Financial Constraints and Emission Intensity *

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Abstract

This paper investigates the impact of tighter financial constraints on firms' emission intensity using an internal capital market perspective. *Winner-picking* incentives can lead to reduced funding for marginal projects within the firm. When clean projects are at the margin this increases emission intensity. I show that, for European firms in emission-intensive sectors, dirtier subsidiaries are more profitable. Exploiting the EBA Capital Exercise in 2011 as a shock to bank credit in a difference-in-difference (DiD) setting, I show that treated firms engage in winner-picking and their clean subsidiaries shrink. But winner-picking is not the only adjustment mechanism if funding access is linked to environmental performance. In this case, firms can shift to cleaner projects to relax financial constraints reducing emission intensity. This mechanism I call *Constraint-minimization*. I model the trade-off between winner-picking and constraint-minimization in a theoretical framework. Finally, I exploit banks' sustainable commitments in a staggered DiD setting, to show that, when credit constraints are related to environmental performance, firms engage in constraint-minimization. The impact of financial constraints on emission intensity therefore depends on the nature of the constraint and firms' internal funding allocation.

Keywords: Financial Constraints, Emission Intensity, Internal Capital Markets, Social Preferences, Bank Credit Supply.

JEL classification: G31, G21, Q54

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1 Introduction

This paper investigates how high-emitting firms react to a tightening in financial constraints and how this impacts their environmental performance, in particular emission intensity. Ex-ante, the impact of reduced access to funding on emission intensity is unclear as two contrasting mechanisms may play a role in determining how firms allocate their resources internally. On the one hand, headquarters can divert funding to relatively more profitable projects, i.e., engage in *winner-picking* (Stein, 1997). For high-emitting firms, this increases emission intensity if the more profitable part of the business is also dirtier. On the other hand, the adjustment can be different if the tightening in access to credit is related to firms' environmental performance. In this case, firms can shift funding to a cleaner part of the business to relax the funding constraint. This incentive I call *constraint-minimization*. This strategy can, however, lead to a decrease in firm per-unit profitability when clean projects are less profitable than dirty ones.

To model firms' internal capital allocation choices and show the trade-off between the two mechanisms, I build a simple theoretical framework. The model starts from the canonical Tirole (2006) setup where agents seeking corporate financing are financially constrained due to agency frictions and limited own resources. I introduce in this setting a clean, less polluting but more costly, project along with a dirty project, which pollutes more but is associated with lower per-unit production costs. The clean and dirty production technologies are modeled following Oehmke and Opp (2023a), however, in this model, rather than having a binary technology choice, the entrepreneur can pursue both the clean and the dirty project. This allows to represent more closely the incentives of more complex firms and capture intensive margin adjustments to changes in access to funding. By introducing changes in access to external financing, I derive testable implications for winner-picking and constraint-minimization incentives: i) when winner-picking prevails average profitability and emission intensity should increase at the firm level, as production declines in the clean, less profitable project; ii) when constraint-minimization prevails, profitability and emission intensity should decline at the firm level, as production declines in the dirty, more profitable project.

In the second part of the paper, I take the model predictions to the data. I first show supporting evidence that clean projects are at the margin for European firms active in emission-intensive sectors. Then I investigate whether firms engage in winner-picking and constraint-minimization when facing tighter financial constraints. As a laboratory, I focus on changes in access to one funding source: bank credit. Using difference-in-differences

(DiD) methodologies, I exploit two natural experiments that led to contractions in credit access. First, I exploit the 2011 European Banking Authority (EBA) capital exercise as an exogenous shock to firms' credit access that is unrelated to firms' environmental performance (Degryse et al., 2021; Gropp et al., 2018). I show results consistent with winner-picking adjustments for treated firms when the constraint-minimization incentive is not present. Second, I exploit banks' sustainability commitments to the Science Based Target Initiative (SBTi) as a shock to credit access for their high-emitting borrowers. I find that firms can engage in constraint-minimization when facing a tightening in credit access that is related to their dirty status.

The theoretical framework allows to better understand the incentives a high-emitting firm faces following a shock to its access to credit. After introducing a benchmark equilibrium with a financially constrained entrepreneur and two projects, I introduce two scenarios. The first scenario is a credit crunch. Capital available to financial intermediaries becomes scarcer and the firm experiences decreased access to external finance. Crucially, this additional constraint is not linked to the firm's emission levels. Hence, this scenario isolates the impact of constraints on firm outcomes when the firm only experiences winner-picking incentives. The firm adjusts by reducing production in the less profitable project, therefore its size decreases but average profitability and emission intensity increase. The second scenario introduces financial intermediaries with social preferences and allows for both incentives to manifest simultaneously. In this scenario, lenders internalize the firms' social costs, therefore financial constraints are stricter for firms associated with higher social costs. Since the credit constraint is related to the firm's emissions level, the firm can reallocate funding in a way that reduces the impact of financial restrictions. This scenario creates two equilibria in the model and a threshold between the two. The threshold is determined by the relative production and social costs of the projects as well as the degree of internalization of social costs by the lenders. If the threshold is not reached, winner-picking incentives prevail and outcomes align with the credit crunch scenario. However, when the threshold is reached, the firm shifts a larger share of the production to the clean project, decreasing emission intensity but also profitability.

To test the model predictions I align the empirical sample to the type of firm in the model and focus on firms active in emission-intensive sectors or with subsidiaries active in these sectors. Financial and ownership information is from Bureau van Dijk's historical ownership database. The data set includes financial and descriptive characteristics of European parent firms based on consolidated reports as well as unconsolidated subsidiary reports. To restrict the sample to applicable firms I exploit data from the European Union's Emission Trading Scheme (EU ETS) which covers emissions from electricity and heat production, as well as other energy-intensive industry sectors. Linking EU ETS data to Bureau van Dijk's historical ownership database, I obtain a sample of European parent firms and their majority-owned European subsidiaries with at least one subsidiary or parent participating in the EU ETS. Subsidiary-level data is exploited to test whether the outcomes at the consolidated parent level are driven by adjustments compatible with the theoretical predictions at the subsidiary level. As the identification strategy exploits changes in access bank credit, I exploit Amadeus Bankers' firm-bank links to identify treated firms in each tested scenario via their main lending relationships.

The models' predictions rest on the assumption that the more dirty part of the business is also the more profitable one. While this will not be the case for all firms in an economy, I show that, for parent firms in my sample, there is a positive relationship between emissions and returns. Dirty subsidiaries are associated with an average of 1.2 percentage points higher ROA and are 89% larger than clean subsidiaries.

The first empirical setting exploits the 2011 EBA capital exercise as a plausibly exogenous shock to firms' credit constraints (Gropp et al., 2018; Degryse et al., 2021). I exploit this event as a natural experiment for the credit crunch scenario, namely a tightening in access to credit unrelated to firms' environmental performance. The exercise was announced in October 2011 and required 61 EU banks to build additional capital buffers to reach a 9% core tier 1 ratio by June 2012. The magnitude and timing of this exercise were unexpected and the EBA continued to monitor participating banks' compliance even after the exercise concluded. The EBA exercise had real consequences for firms dependent on participating banks and led to reduced asset-, investment- and sales growth (Gropp et al., 2018). In this analysis, the treatment group includes firms whose main lender (or lenders) participated in the EBA exercise, while firms with lending relationships with banks that did not participate form the control group. This allows to identify the differential effect of a credit crunch on treated firms' emission intensity relative to a control group of comparable European firms also active in emission-intensive sectors.

The EBA Capital exercise delivers results consistent with winner-picking. Treated firms increase profitability following the shock relative to the control group, which is in line with the idea of firms exploiting internal capital markets to allocate funding efficiently. Moreover, treatment is linked to higher emission intensity driven by a decline in firm size. Evidence at the subsidiary level supports this by indicating that only clean subsidiaries of treated firms shrink in size, while dirty ones develop similarly to untreated ones in terms of emission intensity and emission levels. This shows that firms adjust by decreasing funding to the marginal project and the marginal project is clean.

In the second part of the empirical analysis, I investigate firms' adjustments to a tightening in financial constraints when both winner-picking and constraint-minimization mechanisms are present. For this to transpire, the constraint should be tied to firms' environmental performance. I, therefore, exploit exposure to banks' commitments to lend sustainably in a staggered DiD setting following the methodology proposed by Sun and Abraham (2021). Kacperczyk and Peydró (2021) find that following a commitment to the SBTi, lenders reduce credit supply to high-emitting firms. On that account, I investigate the differential effect of firms' exposure to banks' sustainable commitments on firms' outcomes relative to a control group of similar firms not linked to sustainable lenders.

Treatment in this social preference scenario is linked to a decline in profitability relative to the control group. This indicates that firms do not shrink at the margin when adjusting to this constraint, excluding a winner-picking type of adjustment. Moreover, emission intensity is not significantly impacted following treatment. This is due to a relative size decline accompanied by a proportional reduction in emission levels. In this setting, differently from the credit crunch scenario, treated firms do not actively engage in winner-picking and favor the dirty side of the business in their adjustments. Instead, the evidence suggests firms are catering to lenders' sustainable preferences by engaging in emission reductions, despite the negative implications for profitability. In particular, emission reductions are concentrated at the parent level, where they are more visible. Dirty subsidiaries are not strongly impacted, however, following treatment, the number of intermediary ownership links between parents and their dirty subsidiaries increases. Treated parents therefore reduce visible emissions while increasing their distance from less visible ones. These results are consistent with a constraint-minimization behavior being undertaken to improve access to funding as emission reductions at the borrower level might be a better signal to sustainable lenders aiming to green their portfolios.

The empirical results support the model predictions and highlight that when high-emitting firms face a tightening in access to credit they allocate funding within the firm to adjust to this constraint. On the one hand, if the constraint is unrelated to social costs, treated firms adjust following winner-picking incentives, they shrink at the margin and this leads to an increase in emission intensity. On the other hand, when firms face a credit constraining shock due to lenders' social preferences firms do engage in a constraint-minimization behavior. In this case, firms do not shrink at the margin and experience a temporary dip in profitability relative to similar firms that are not linked to lenders with sustainable commitments. This evidence supports the hypothesis that internal capital market decisions play a role in determining firms' environmental performance. Moreover, they provide further proof that, for firms active in high-emitting sectors, clean projects are at the margin.

In this paper, I focus on emission intensity as a leading indicator for firms' environmental performance. A reason for this is that I investigate firms' adjustments to worsening funding conditions. When firms shrink, a decline in emission levels is not necessarily an indicator of better environmental performance at the firm level. Performance improves when the decline in emissions is more than proportional to the size decline. A potential critique of this paper is that, ultimately, if society's objective is to reduce emissions, increasing funding constraints for high-emitting firms may achieve this objective even if some firms become more emission-intensive as a result. While this might be true in principle, governments may not only be interested in the tagline emission reductions but also in limiting the socio-economic risks associated with a sustainable transition. The EU, for instance, introduced in 2021 the Just Transition Mechanism (JMT), which, among other things, protects and supports firms active in high-emitting sectors. If tightening access to credit reduces firms' incentives to invest in their clean marginal project, then this is clearly in contrast with the transition-support goal of the JMT.

This work is relevant for the design of prudential regulation in the financial sector to manage exposure to transition risks. Several of the regulatory interventions discussed by regulators and supervisory institutions, such as dirty capital requirements, mandatory reporting on risk exposures, or central bank portfolio decarbonization, can impact credit access for emission-intensive firms as modeled in the social preferences scenario. My paper points to a potential unintended consequence of these interventions, which policymakers should be mindful of in policy design. When the tightening in financial constraints is not significant enough to trigger a shift to constraint-minimization incentives, emission-intensive firms may continue to protect their dirty projects and reduce investments in the clean side of their business. This allows them to maintain profitability in the short run despite facing tighter financing conditions. Oehmke and Opp (2023b) highlight a similar unintended consequence at the bank level in their theoretical investigation of capital requirements targeting carbon-intensive lending. This issue arises as long as clean investments are at the margin for dirty firms (or clean firms are at the margin for lenders in Oehmke and Opp (2023b)). In the context of facilitating a transition to a more sustainable economy, it is therefore important to evaluate what consequences these policies could have for internal funding allocation choices of high-polluting firms and their incentives to invest in their clean and more sustainable projects.

A related strand of theoretical papers investigates and compares how regulatory interventions can impact firms' environmental performance in a setting where firms can be financially constrained (Döttling and Rola-Janicka, 2023). In this setting, Oehmke and Opp (2023a) investigate the impact of sustainable investors, while Allen et al. (2023) introduce a political economy perspective by considering the impact of political support for regulatory intervention. Finally, Heider and Inderst (2023) introduce a product market perspective and consider policy implications for industry distribution. Differently from these papers, I do not focus on optimal interventions, but rather on the mechanisms and incentives behind within-firm capital allocation and their consequences for firms' performance. I also provide empirical evidence of within-firm adjustments to changes in access to credit supporting the assumptions and predictions of the theoretical framework.

My paper is also closely related to the strand of climate finance papers that investigate changes in firms' environmental outcomes around shocks to credit availability. Exploiting events that extend firms' access to credit Goetz (2019) and Levine et al. (2018) show an improvement in environmental outcomes for treated firms. Complementing these findings, De Haas et al. (2021) show that credit constraints can be an obstacle to firms' green investments, as carbon emissions decrease less in localities where access to credit is scarcer. The closest paper in this literature is Kacperczyk and Peydró (2021), which investigates the impact of lenders' SBTi commitments on firms' outcomes. Using a sample of large, international, and listed firms the authors find that exposed firms decline in size but do not reduce emissions and show an increase in profitability. While divergent from the results in this paper, the results in Kacperczyk and Peydró (2021) are aligned with the predictions in the social preferences scenario of the model and consistent with winner-picking incentives prevailing for the firms in their sample. This work also relates to papers that investigate firms' reactions to changes in transition risk exposure. In particular Berg et al. (2023) show that divestment of dirty assets is the main driver of emission reductions following the Paris Agreement. Similarly, Duchin et al. (2023) also link environmental pressure with the divestment of dirty assets.

My paper differs from the previous work in this area as I provide a structured investigation of the mechanisms that drive within-firm reallocation of funding following a shock to credit constraints. I provide a theoretical framework as well as empirical evidence, to show that when clean projects are at the margin for dirty firms, two potential mechanisms arise in how firms adjust with diverging implications for environmental performance.

Another strand of literature related to this project is the one regarding access to internal capital markets and funding choices of firms. My work relates to the seminal work by Stein (1997) which introduces the theoretical argument for headquarters' incentives to engage in winner-picking. More recent work further confirms the relevance of internal capital market influence on funding allocation for cross-subsidization (Kabbach-de-Castro et al., 2022), to protect subsidiaries with better investment opportunities (Gugler et al., 2013) or to those with higher marginal revenue (Giroud and Mueller, 2019). I contribute to this strand of literature by providing a scenario in which engaging in winner-picking can worsen the capital constraint the firm is facing. In this case, I propose the alternative incentive of constraint-minimization, highlighting a trade-off between profitability and access to funding. Moreover, I propose a setting in which capital reallocation via internal capital markets is directly linked to firms' negative environmental externalities.

2 A simple model with capital constraints and multiple projects

In order to better understand the incentives a high-emitting firm faces following a shock to its access to credit, in this section, I introduce a simple static model. Starting from a canonical Tirole (2006) setup, the entrepreneur in the model is financially constrained due to agency frictions and limited own resources. Following Oehmke and Opp (2023a), I introduce in this setting a "clean", less polluting but more costly project along with a "dirty" one, which pollutes more but is associated with lower per-unit production costs. Characterizing the polluting project as the more profitable is perhaps not a reasonable assumption for all firms, however, the model attempts to sketch the incentives of high-emitting firms for which this assumption is more likely to hold. The implications of this model assumption are thoroughly discussed at the end of this section and evidence supporting the assumption is provided in the empirical section.

The entrepreneur, the projects, and the financial intermediaries A risk-neutral entrepreneur is protected by limited liability and owns assets of value A. She has access to two profitable projects $j \in \{C, D\}$ with identical positive cash flows $R \cdot min(K_j, \bar{K})$, where K_j is the production level. Following Oehmke and Opp (2023a), the return function is a simple form of decreasing returns to scale, where the return is linearly increasing until the optimal production level $\bar{K}$ is reached. Once $\bar{K}$ is produced, the marginal return of each additional unit is equal to zero. Hence, there is no incentive to produce beyond the optimal amount in each project. The projects are independent of one another and, for each, the returns realize with probability p if the entrepreneur exerts effort.[1] With probability $1-p$ returns are zero. If the entrepreneur chooses to shirk (i.e. not exert effort) she obtains a private benefit BK_j for each project where she shirks. However, when she does, the probability that the project succeeds decreases by Δp, where $p > \Delta p > 0$. While the production level in each project is observable, the decision of the entrepreneur at the moral hazard stage is not verifiable.

The two projects that the firm can pursue offer identical cash flows, but they differ with respect to production costs and social costs. Per unit, project D has lower production costs ($0 < k_d < k_c$) but higher social costs ($0 \leq \theta_c < \theta_d$). In both projects, for production levels below $\bar{K}$, marginal profits $\pi_j = pR - k_j$ are positive. For simplification, I assume that the entrepreneur disregards social costs, hence if she were not capital constrained the optimal production level in both projects would be $\bar{K}$.
To limit agency cost such that there is a finite production scale and rule out equilibrium shirking I make the following assumption:

Assumption 1: *For each project j per unit of capital:*

$$\pi_j < \frac{pB}{\Delta p} < pR - \frac{p}{\Delta p}\pi_j \tag{1}$$

The left-hand side inequality imposes that in each project per unit agency costs are larger than marginal profits, ensuring that the projects can be funded. The right-hand side inequality imposes that per unit profit loss due to shirking is larger than per unit pledgeable income so that the agency problem must be controlled to achieve funding. Furthermore, I assume that the value of the initial assets of the entrepreneur must be within the following interval:

Assumption 2: *The entrepreneur's initial assets A are such that:*

$$k_d\bar{K} - p\bar{K}(R - \frac{B}{\Delta p}) < A < k_c\bar{K} + k_d\bar{K} - 2p\bar{K}(R - \frac{B}{\Delta p}) \tag{2}$$

This ensures that the entrepreneur is financially constrained and guarantees that for

[1] I assume that the entrepreneur is not able to cross-pledge for simplicity: i.e. pledge the income of one project as collateral for the other. In Appendix A.4, I relax this assumption and show that it does not impact the model predictions. Cross-pledging is also addressed in the model discussion in Section 2.

parameter values satisfying this condition, the solution includes equilibria where the entrepreneur chooses to produce in both subsidiaries. Specifically, the first inequality ensures that the entrepreneur has enough own assets to obtain external finance and produce $\bar{K}$ in D and a positive amount in project C. When A is below the lower bound, the entrepreneur produces $K_d < \bar{K}$ in project D and nothing in project C as marginal profits in project D are higher and the entrepreneurs' utility only depends on financial profits. The second inequality ensures that the entrepreneur cannot finance both projects with her own assets up to $\bar{K}$ so external capital is always necessary. Finally, even with external capital, the entrepreneur does not have sufficient pledgeable assets to produce $\bar{K}$ in both projects. Hence, she is financially constrained.

To obtain financing the entrepreneur can resort to financial intermediaries. In the model, there is a continuum of perfectly competitive financial intermediaries. In the baseline, all lenders maximize profits and disregard social costs. The latter may appear to be a strong assumption, however even if lenders had social preferences they may disregard them due to free-riding incentives or competition from other lenders that only maximize profits (Oehmke and Opp, 2023a; Degryse et al., 2022).

Baseline equilibrium The entrepreneur's objective is:

$$\max_{R_e^c, R_e^d, K_c, K_d} \qquad pR_e^c + pR_e^d - A. \tag{3}$$

She selects production levels (K_c,K_d) and entrepreneurs' payoffs (R_e^c, R_e^d) to maximize her utility subject to her own incentive compatibility (IC) constraints and the lenders' individual rationality (IR) constraints:

$$\begin{aligned}
&IC1: \ pR_e^c \geq (p - \Delta p)(R_e^c) + BK_c, \\
&IC2: \ pR_e^d \geq (p - \Delta p)(R_e^d) + BK_d, \\
&IC3: \ p(R_e^c + R_e^d) \geq (p - \Delta p)(R_e^c + R_b^d) + B(K_c + K_d), \\
&IR1: \ p(RK_c - R_e^c) \geq K_c k_c - a_c \\
&IR2: \ p(RK_d - R_e^d) \geq K_d k_d - a_d \\
&IR3: \ p(RK_c - R_e^c) + p(RK_d - R_e^d) \geq K_c k_c + K_d k_d - A
\end{aligned}$$

where a_c and a_d are the entrepreneurs' own funds invested in each project and $a_d + a_c = A$.[2] The first two incentive compatibility constraints (IC1, IC2) ensure that the entrepreneur does not shirk in either project, while the third (IC3) ensures that she does not shirk in both. IC3 is a less stringent condition than IC2 and IC1, therefore it is satisfied when the first two are. The IR constraints similarly ensure that the expected total return on investment minus the payoff for the borrower in the clean project (IR1), the dirty project (IR2), or both (IR3), is at least equal to the borrowed funds for the respective projects. Where borrowed funds correspond to capital expenditures not funded with the invested capital of the borrower. Simply put, the lender participates as long as in expectation its payoff is at least equal to the loan amount. IR3 is satisfied if IR2 and IR1 are.

The problem can be simplified as in the baseline the entrepreneur always prefers to produce $\bar{K}$ in project D. This is highlighted in the following Lemma.

Lemma 1: *The entrepreneur always prefers to produce in project D over project C for $K_d < \bar{K}$.*

Since the dirty project delivers higher marginal utility to the entrepreneur than the clean one for levels of production below $\bar{K}$, the entrepreneur will produce a positive amount in C only if she produces $\bar{K}$ in project D. This holds for the optimal contract that allows the entrepreneur to extract the NPV of the project. A formal proof is provided in Appendix (A.1). The return functions as specified therefore introduce a clear ranking between projects, with the clean project at the margin. When the entrepreneur produces $\bar{K}$ in D, she invests $a_d = \bar{K}\left(k_d - p(R - \frac{B}{\Delta p})\right)$ and her utility $U^d_{e,max}$ is equal to the total surplus of the project ($\bar{K}(pR - k_d)$) as there is perfect competition among financial intermediaries.

Assumption 2 ensures that the entrepreneur has sufficient own assets A to also produce a positive amount in project C. Hence, the entrepreneur produces $\bar{K}$ in D using a_d of her

[2]The entrepreneur always invests all her wealth A as this maximizes access to external finance (Tirole, 2006).

own funds and chooses the production level and payoff in C that maximizes her utility:

$$\begin{aligned}
\max_{R_e^c, K_c} \quad & U^d_{e,max} + pR^c_e - a_c \\
\text{subject to} \quad & IC1: \; R^c_e \geq \frac{BK_c}{\Delta p}, \\
& IR1: \; p(RK_c - R^c_e) \geq K_c k_c - a_c
\end{aligned}$$

In equilibrium both remaining constraints are binding and the entrepreneur produces a positive amount in project C equal to:

$$K_c^* = \frac{a_c}{k_c - p(R - \frac{B}{\Delta p})} \tag{6}$$

The optimal level of production in the clean project K_c^* is limited by the entrepreneur's investment in the dirty project (since $a_c = A - a_d$). Hence, if the optimal level of production in project D increases the entrepreneur will produce less in project C. Similarly K_c^* decreases in both production costs (k_c and k_d) as well as agency costs. Production in C increases with a higher initial endowment A or higher expected cash-flows pR. See Appendix (A.1) for a more detailed solution.

Credit Crunch Scenario The first extension to the baseline introduces a credit crunch scenario where the firm experiences a decrease in access to credit which is not linked to its own social costs. This allows for isolating the entrepreneur's winner-picking incentives and observing the implications for firm outcomes and in particular for emission intensity.

Similarly to the seminal model by Holmstrom and Tirole (1997), a credit crunch is introduced by a reduction in the total capital available to intermediaries. Capital scarcity in turn leads to positive profit for financial intermediaries. In the baseline of this model financial intermediaries make no returns, their payoff is equal to the loan amount, as there is perfect competition and capital is not scarce.[3] Following a credit crunch, capital scarcity causes the rate of return for lenders (r_b) to increase. This, in turn, tightens the lenders' IR constraint as the minimum payoff for the lender now corresponds to the loan amount plus a positive return on investment. To limit the potential severity of this scenario I assume that $r_b < \pi_j/k_j$ for $j \in D, C$, so that the entrepreneur can access enough external capital to produce in both projects despite the credit crunch.[4]

[3] The zero-returns assumption is a simple normalization and can be made without loss of generality.

[4] In a more severe credit crunch scenario, production in the less profitable project is abandoned and

With a credit crunch, the entrepreneur maximizes her utility as in the baseline but is subject to stricter IR constraints:

$$IR1^{CC}: \; p(RK_c - R_e^c) \geq (K_c k_c - a_c)(1 + r_b)$$
$$IR2^{CC}: \; p(RK_d - R_e^d) \geq (K_d k_d - a_d)(1 + r_b)$$

The credit crunch shifts to the lender part of the total surplus of the project equal to the required return on the loan amount and increases the per unit own assets the entrepreneur invests. However, the tighter lender participation constraints do not impact the relative ranking of the two projects. Lemma 1 still applies and the entrepreneur continues to obtain more utility from producing in project D with the same own asset investment compared to project C for levels of production below $\bar{K}$ in D. It follows then that, in a credit crunch, the entrepreneur protects the more profitable investment and continues to produce the optimal production $\bar{K}$ in D. With the remaining own funds the entrepreneur produces in C, however, production decreases, so that the credit crunch equilibrium K_c^{CC} is smaller than the baseline K_c^*:

$$K_c^{CC} = \frac{a_c^{CC}(1 + r_b)}{k_c(1 + r_b) - p(R - \frac{B}{\Delta p})} \tag{8}$$

A detailed derivation of this equilibrium is provided in Appendix (A.2) along with proof that K_c^{CC} is smaller than the baseline K_c^*.

Following a tightening in access to credit that is unrelated to the firm's social costs, the more severe the credit crunch is the more the entrepreneur shrinks its production in project C, while protecting production in project D. The firm's overall production level declines, however winner-picking incentives lead to an increase in average profitability and in average social costs per unit produced. This is driven by the fact that a larger share of total production after the shock occurs in the project with higher marginal returns and marginal social costs. I summarize these predictions in the following proposition:

Proposition 1 (Credit Crunch Predictions): *Following a tightening in access to credit that is not caused by the firms' own social costs, the entrepreneur decreases production in project C while protecting production in project D. Hence, following a credit crunch:*

the entrepreneur maximizes production in one project only.

(i) Firm profitability increases as a larger share of production takes place project D with higher marginal profit.

(ii) Firm social cost intensity increases as a larger share of production takes place project D with higher social costs.

Social Preferences Scenario The entrepreneurs' reaction to a tightening in access to credit may differ if the tightening is a consequence of the firm's own social costs. Recent empirical literature shows that firms associated with higher social costs may be facing growing restrictions in their access to funding (Bolton and Kacperczyk, 2021; Ceccarelli et al., 2020; Chava, 2014; Delis et al., 2021; Kacperczyk and Peydró, 2021; Krueger et al., 2020; Mueller and Sfrappini, 2022; Seltzer et al., 2022). The reaction to this type of constraint can differ compared to the credit crunch scenario where an exogenous shock causes a contraction in credit. Differently from the scenario above where the entrepreneur only faced winner-picking incentives, when there is a link between financial constraints and social costs the entrepreneur can optimize by also following a constraint-minimization strategy.

In this scenario, I, therefore, investigate whether tighter credit constraints caused by the firms' social costs have different implications for firm outcomes and emission intensity compared to a simple credit crunch scenario. To this end, I introduce social preferences to the financial intermediaries in the model. Financial intermediaries now internalize social costs θ_c and θ_d with intensity γ, where $0 < \gamma \leq 1$. To limit the potential severity of this scenario I assume that $\pi_j - \gamma\theta_j > 0$ for $j \in \{D, C\}$, such that the internalized social costs do not outweigh the financial value for either project.

With socially oriented intermediaries, the entrepreneur maximizes her utility as in the baseline but is subject to stricter IR constraints:

$$IR1^{SP}: \; p(RK_c - R_e^c) \geq K_c k_c - a_c + \gamma\theta_c K_c$$
$$IR2^{SP}: \; p(RK_d - R_e^d) \geq K_d k_d - a_d + \gamma\theta_d K_d$$

This modification to the baseline can lead to a shift in the relative attractiveness of the two projects for the entrepreneur even if she does not have social preferences herself. Hence, Lemma 1 does not always apply. Instead, this scenario introduces a threshold:

$$\gamma^* = \frac{k_c - k_d}{\theta_d - \theta_c} \tag{10}$$

which depends on the relative production and social costs of the two projects. When $\gamma \leq \gamma^*$, the ranking of the two projects remains unchanged and the entrepreneur continues to prioritize production in D as in the baseline. When $\gamma > \gamma^*$, constraint-minimization incentives invert the ranking of the two projects, such that the entrepreneur produces $\bar{K}$ in C. In both cases, given the production $\bar{K}$ in project i the entrepreneur chooses the level of production K_j^{SC} in the other project. She now maximizes her utility subject to a tighter lender's IR that reflects banks' internalization of a share of the social costs of production. This leads to a new equilibrium K_i^{SP} where $i, j \in \{D, C\}$ and $i \neq j$:

$$K_i^{SP} = \frac{A - \bar{K}\left(k_j + \gamma\theta_j - p(R - \frac{B}{\Delta p})\right)}{k_i + \gamma\theta_i - p(R - \frac{B}{\Delta p})} \tag{11}$$

All derivations and proofs of this equilibrium can be found in Appendix (A.3).

When $\gamma \leq \gamma^*$, winner-picking incentives prevail also in this scenario with intermediaries with social preferences. Lemma 1 applies and the entrepreneur produces K_c^{SP} in project C and $\bar{K}$ in project D. K_c^{SP} is lower than the baseline K_c^* due to internalized social costs. Therefore, akin to the credit crunch scenario, social preferences can also lead to lower production levels, higher profitability, and an increase in average social costs per unit produced.

However, if the degree of internalization of social cost γ reaches the threshold γ^* defined in Equation 10, constraint-minimization incentives prevail inverting the ranking of the two projects. The entrepreneur tilts toward producing more in project C ($\bar{K} > K_c^*$), and reduces production in project D ($K_d^{SP} < \bar{K}$) to be able to access more external financing. This decreases average profitability but also social cost intensity at the firm level. These results are summarized in the following proposition:

Proposition 2 (Social Preferences Predictions): *Following a tightening in access to credit that is caused by the firms' own social costs, there are two possible equilibria:*

- ***Winner-picking equilibrium****: If $\gamma < \gamma*$ the entrepreneur decreases production in project C. Hence:*

  (i) Firm profitability increases as a larger share of production takes place project D with higher marginal profit.

  (ii) Firm social cost intensity increases as a larger share of production takes place project D with higher social costs.

- ***Constraint-minimization equilibrium**: If $\gamma \geq \gamma*$ the entrepreneur produces the optimal amount $\bar{K}$ in project C and reduces production in project D. Hence:*

  (i) Firm profitability decreases as a larger share of production takes place project C with lower marginal profit.

  (ii) Firm social cost intensity decreases as a larger share of production takes place project C with lower social costs.

A few parameters impact the likelihood that the threshold in the model is reached. In particular, all else equal firms with very profitable (clean) dirty projects are (more) less likely to reach the threshold and invert the relative ranking of the two projects when facing this type of constraint. Similarly, the threshold is less likely to be reached if the cleaner project is not too different from the dirty one in terms of social costs or if the share of internalized social costs by lenders is too low. When possible, these relevant characteristics are exploited in the empirical analysis to identify firms that are more likely to engage in constraint-minimization or winner-picking when facing a tightening in access to credit that is related to their social costs.

Discussion and model extensions Before testing the predictions of the model in an empirical setting it is important to discuss some of the assumptions made in the theoretical setting and their implications. Importantly, the theoretical predictions rely on the assumption that for emission-intensive firms the marginal project is clean. In this model, since marginal return is always higher in the dirty project until optimal production, winner-picking incentives will always trigger a reduction in clean production in the credit crunch scenario. It is clear then that inverting the relative profitability ranking of the two projects would also invert this prediction. This means that, in cases where the clean project is relatively more profitable than the dirty one for production levels lower than $\bar{K}$, a decline in access to funding will decrease production in the dirty project. This is perhaps not so surprising as in equilibrium this will also be a firm that specializes in clean production.

A more interesting case is a firm that specializes in dirty production but decreases production in the dirty project more than in the clean one when facing a credit crunch scenario. This will happen in the model if the return functions of the two projects have a different shape. So far, cash flows of the form $R \cdot min(K_j, \bar{K})$, allowed for the marginal return of project D to be always higher than the marginal return of project C for $K_d < \bar{K}$. This assumption introduced a clear ranking of the two projects. This result does not apply to more standard decreasing return functions, as the ranking will always hold for the same level of production but can invert when the production level in the two projects differs. To see this, let's assume more standard decreasing return functions $R_c(K)$ and $R_d(K)$ where: $R_c'(K) > 0$, $R_d'(K) > 0$, $R_c''(K) < 0$, $R_d''(K) < 0$, and, for the same K, $R_c'(K) < R_d'(K)$ and $R_c''(K) > R_d''(K)$. In equilibrium, the financially constrained entrepreneur will maximize utility by producing K_c^* and K_d^* such that $R_c'(K_c^*) = R_d'(K_d^*)$. In equilibrium we will observe a similar firm as in the baseline, that produces more in the dirty project and less in the clean one. However, if this firm faces a credit crunch, the entrepreneur will reduce production in the dirty project more than in the clean one. This is because in the new equilibrium, the marginal returns of the two projects will be equal and lower and the marginal return in the dirty project decreases less quickly in K than the clean one. This reverses the predictions in Proposition 1. This sensitivity of the model predictions to the marginal project assumption highlights the first contribution of the empirical analysis. Testing how the firm adjusts to a tightening in access to funding (unrelated to the firms' social costs), allows to identify the marginal project of the firm. Hence, if in a credit crunch scenario, the firm becomes more emission-intensive the empirical results will lend support to the original model assumption of a strict ranking between projects.

Currently, the model does not include any diversification benefit from having both projects under one roof. However, the mechanisms and predictions are robust to the inclusion of cross-pledging. This is one of the benefits of an internal capital market and has been modeled and shown to decrease capital constraints relative to projects with individual funding (Tirole, 2006; Cestone and Fumagalli, 2005; Kabbach-de-Castro et al., 2022). With cross-pledging the entrepreneur is able to pledge the income of one project as collateral for the other. Cross-pledging allows the entrepreneur to achieve a higher level of financing relative to the case where the entrepreneur finances each project individually. However, the mechanisms of winner-picking and constraint-minimization are also present under cross-pledging and lead to equivalent predictions compared to the simpler setting. Derivations can be found in Appendix (A.4).

3 Empirical Analysis

The theoretical setup in this paper delivers a series of testable implications. First of all, a relevant question is whether for high-emitting firms dirty projects are indeed more profitable than clean ones. I introduce this ranking as a fundamental assumption, which is driving the main implications of the model. Hence, testing whether this ranking is observable in the data is the first step in confirming the applicability of the model implications in an empirical setting. A second contribution of the empirical analysis is to test whether firms indeed engage in winner-picking as the model predicts in a credit crunch setting. By introducing a plausibly exogenous shock to credit access that is uncorrelated with the firms' emission intensity, I can test whether firms adjust at the margin (i.e., increase average profitability) and whether the marginal project is clean (i.e., increase emission intensity). By exploiting information at the subsidiary level I can also confirm whether clean subsidiaries shrink relatively more than dirty ones. Finally, by introducing a shock to credit access correlated with firms' emission intensity, I can test the implications of the social preference scenario in the data. In particular, I can test whether firms react differently to this type of constraint and whether they engage in constraint minimization.

In this section, I first introduce the data and provide evidence that for the firms in my sample, the more emission-intensive part of the business is also the more profitable one. Then I introduce two natural experiments to test the predictions of the credit crunch and the social preferences scenarios delineated in the model. To test the credit crunch predictions, I exploit the EBA Capital Exercise announced in October 2011. This event represented a credit crunch for exposed firms as shown by Gropp et al. (2018). Finally, to test the social preferences predictions, I exploit firm exposure to changes in lenders' sustainable preferences, proxied by commitments to SBTi.

3.1 Data

The model's predictions will not apply to all firms. Instead, the mechanisms of winner-picking and constraints-minimization as modeled in the previous section should mainly apply to firms active in high-emitting sectors. To identify a sample of applicable firms I exploit data from the EU ETS. The EU ETS collects emissions information at the installation level for installations located in the European Union plus Iceland, Liechtenstein, and Norway (EEA-EFTA states[5]). Specifically, the EU ETS covers CO_2 from electricity and heat generation and energy-intensive industry sectors. Since 2013, commercial aviation within the European Economic Area and other greenhouse gases such as nitrous oxide (N_2O) and perfluorocarbons (PFCs) from industrial production are also included. This

[5]Switzerland is excluded in this analysis as it linked its emission trading scheme to the EU ETS only in 2020.

corresponds to 39% of the EU's total greenhouse gas emissions (European Commission, 2020).

Linking EU ETS emission data to Bureau van Dijk's (BvD) Ownership Database, I obtain a sample of European parents and their European subsidiaries with at least one subsidiary or parent participating in the EU ETS.[6] The BvD Ownership Database includes historical ownership links as well as descriptive and financial characteristics at the parent- and subsidiary-level for reporting subsidiaries. I restrict the sample to only include majority ownership links and the distance between parents and subsidiaries to a maximum of 5 links in the ownership chain, although the majority of links are direct ones (52%).

The sample includes 556 parent firms reporting consolidated financial statements in the period between 2009 and 2019. At the subsidiary level, the financial statements are unconsolidated, and, after excluding subsidiaries in the financial sector (SIC codes between 6000 and 6999), the sample covers 3,559 parent-subsidiary relationships. While financial information at the subsidiary level depends on whether the subsidiary reports independently, ownership information has wider coverage. Therefore parent-level emissions are aggregated emissions across the ownership chain, regardless of whether subsidiaries are reporting financial information or not. While the sample of firms in this data only covers around 3% of entities participating in the EU ETS, the sample is representative with respect to the distribution of emissions across different-sized firms and the relative share of high-, mid-, and low-emitting firms (see Figure B1 in Appendix B).

An advantage of employing the Bureau van Dijk's (BvD) Ownership Database is that it encompasses private companies and therefore includes a larger share of smaller and medium enterprises compared to other studies that focus on large listed companies. This focus on non-listed firms is an advantage given the crux of this empirical exercise is firms' adjustments to changes in access to bank financing. While it is plausible that listed firms may be able to mitigate the impact of the credit-constraining shocks from their main banking relationships through their access to other capital markets, non-listed firms are less likely to be able to substitute for other sources of funding. A further advantage of the final dataset linking BvD to EU ETS is that it allows observing both parent-level aggregate adjustment to changes in access to funding, as well as within-firm adjustments at the subsidiary level. Not only with regard to financial decisions but also in terms of

[6] I thank Daniel Streitz and Lin Ma for generously sharing their matching file. Subsidiaries located outside of EEA-EFTA states and EEA-EFTA subsidiaries that do not report financial information independently are not included in the sample.

emission outcomes.

To construct exposure measures to the above-mentioned shocks I link the parent firms in my sample to the Amadeus Bankers dataset. This data set reports firms' main lending relationships as reported by chambers of commerce and firm registries in European countries and complemented with phone interviews with the firm representatives. I employ a vintage of this data from 2012 to reduce potential noise in the estimation compared to using current data, however, Giannetti and Ongena (2012) compare different vintages and show that bank-firm relationships are extremely sticky in this data set.

Table 1 reports summary statistics at the parent and subsidiary level for the main variables employed in the analysis. Subsidiaries are defined as *Dirty* if they own one or more installations participating in the EU ETS, while all other subsidiaries are considered *Clean*. The two types of subsidiaries differ with regard to several characteristics, with dirty subsidiaries having higher levels of size, profitability, and tangibility. Table B1 in the Appendix includes all variable definitions. Table B2 shows the distribution of firms by country and industry. All financial variables are winsorized at the 5% level following Gropp et al. (2018) and Acharya et al. (2018).

[Table 1]

The models' predictions rest on the assumption that the more emission-intensive part of the business is also the more profitable one. This will clearly not be the case for all firms in an economy, however, Figure 1 provides indicative evidence that the assumption holds in this sample. The left graph shows the distribution of ROA at the subsidiary level, conditional on the subsidiary being dirty (in red) or clean (in green). The dirty distribution is shifted to the right, such that dirty subsidiaries are less likely to have negative ROAs but more likely to have positive values. Further evidence of a positive relationship between emissions and returns in this sample is provided in the right-side graph. This shows a positive correlation between emission intensity and ROA at the subsidiary level.

[Figure 1]

Given the positive correlation between profitability and the dirtier side of the business, in the model's baseline equilibrium production in the dirty project is larger. Within-firm evidence of this positive correlation between dirty subsidiaries and profitability and size in this sample is provided in Table 2. When accounting for time-varying parent characteristics, as well as the industry and location of subsidiaries using respectively parent-year, industry, and country fixed effects, dirty subsidiaries are associated with an average of 1.2 percentage points higher ROA (Column (1)) and are 89% larger compared to clean subsidiaries (Column (2)).

[Table 2]

3.2 A Credit Crunch Scenario: The EBA Capital Exercise

To test the predictions of the credit crunch scenario, I exploit the 2011 European Banking Authority (EBA) capital exercise as a plausibly exogenous shock to firms' credit constraints. The exercise was announced in October 2011 and required 61 EU banks to build additional capital buffers to reach a 9% core tier 1 ratio by June 2012. The magnitude and timing of this exercise were unexpected and the EBA continued to monitor participating banks' compliance even after the exercise concluded (Gropp et al., 2018). The 9% requirement was reported by the Financial Times as well above financial analysts' predictions and as likely to lead to a €275 billion combined capital shortfall for participating banks, according to Morgan Stanley estimates (Jenkins et al., 2011). Participating banks were not selected based on their current health or recent events. Instead, the selection criterion was based on country-relative size: banks representing the largest market share by total assets at the end of 2010 were selected such that for each EU Member State 50% of the banking sector was included in the exercise.

The lack of anticipation, the unexpected magnitude of the requirement, and the selection criteria for participating banks make this event an optimal natural credit crunch experiment in my setting. This event has been investigated in the literature. In particular, Mésonnier and Monks (2015) show that banks' efforts to comply with the requirements led to a credit crunch in the euro area as non-participating banks did not substitute for constrained lenders. Moreover, Gropp et al. (2018) find that banks reduced their risk-weighted assets by shrinking corporate lending volumes in order to comply with the exercise requirements. This led to real consequences for firms dependent on participating banks and reduced asset-, investment- and sales growth.

Exploiting the Amadeus Bankers firm-bank link, I construct an indicator of firms' exposure to participating banks. A complete list of the banks included in the exercise and present in the Amadeus Bankers database is included in Appendix Table B3. Following Gropp et al. (2018), I exclude acquired banks, banks that received a capital injection during the pre-treatment period, and banks with negative levels of equity. I also consider lending relationships with subsidiaries of participating banks as sources of treatment exposure. The exercise is conducted at the highest level of consolidation, however, Degryse et al. (2023) show that participating banks also reduce subsidiaries' lending to achieve the 9% requirement.

I consider a firm *Treated* if the firm's main lender (or lenders) participated in the EBA Exercise. The control group is then composed of firms whose main lenders did not participate in the exercise or had lending relationships with lenders that did not participate. This allows comparing exposed firms' reactions to a reduction in credit access to a control group of firms also active in polluting sectors in the EU. The baseline regression employs a DiD approach to estimate the impact of this shock on exposed firms' outcomes:

$$Y_{ft} = \beta_1 Treated_f \times Post_t + \zeta_f + \zeta_{it} + \zeta_{lt} + \varepsilon_f. \tag{12}$$

where the indicator for *Post* is equal to one in the post-treatment period which is the year 2012. There are two main reasons for the short post-treatment period. A practical reason is that the EU ETS reporting changed in 2013, as the scheme advanced from Phase 2 to Phase 3. Phase 3 widened both the reporting sectors as well as the type of emissions covered. Hence, emission data from 2013 onward is not comparable to the previous years. The second reason regards the nature of the shock used for this scenario. While the EBA Capital Exercise represents a quasi-natural experiment with the potential for a credit crunch in the short term, in the longer run participating banks may prefer to raise their equity levels rather than continue to contract lending, and constrained firms may create new lending relationships or resort to other forms of financing.

The specification includes firm as well as industry-year and location-year fixed effects. This controls for unobservable time-invariant characteristics at the firm level, as well as time-varying trends at the industry and country level. The main dependent variables are ROA and Emission Intensity. These variables represent firms' profitability and social cost intensity in the data and allow to test the model propositions. In the empirical analysis, I furthermore decompose the impact on emission intensity by distinguishing between the impact on emission levels and on firm size. This analysis covers the period between 2009 to 2012.

Once the impact of a credit crunch on firm outcomes is observed, it is also possible to scrutinize whether it realizes as the mechanism in the model predicts. If the firm's marginal project is clean, winner-picking incentives should prevail in a credit crunch and the firm should reduce funding for cleaner subsidiaries, while protecting dirty ones.

After observing the baseline effect at the consolidated parent level, I zoom into within-group effects using subsidiary information. Specifically, I test if the credit crunch has a differential impact on the size of dirty and clean subsidiaries of treated parents.

3.3 Results: The EBA Capital Exercise

In this section I exploit the EBA capital exercise as a natural credit crunch experiment to test the predictions in Proposition 1. The model predicts an increase in profitability and emission intensity for firms exposed to a credit crunch when their marginal project is clean and they adjust following winner-picking incentives. Table 3 reports the results of the preferred baseline specification outlined in Equation (12) estimated on the baseline sample of non-listed parents with consolidated financial reports and aggregated emission data from the EU ETS. Column (1) shows that treatment is linked with an increase in profitability of 1.5 percentage points relative to the control group. This is consistent with winner-picking mechanisms at play. Column (2) shows that in this sample a credit crunch also leads to a relatively higher emission intensity. This is consistent with the marginal project being relatively less polluting. Treated firms are associated with 0.29 kt (kilotonne) of CO_2/Mil US$ higher emission intensity after treatment compared to the control group. This differential effect is sizable as it equals around half of the sample mean. The last two columns highlight the reason for this pronounced effect by decomposing it. Results show that the relative increase in emission intensity is driven by a decline in total assets (Column (3)) while there is no significant difference in emission levels relative to the control group (Column (4)).

[Table 3]

These first results highlight firms' reactions to treatment consistent with Proposition 1. Following a credit crunch treated firms shrink relatively to the control group, however, emissions do not experience a similar reduction. These results are consistent with winner-picking as outlined in the model. Treated firms react to the credit crunch by adjusting at the margin, therefore average profitability increases. Moreover, the marginal project appears to be clean as the reduction in size is not coupled with a significant reduction in emission levels.

Information at the subsidiary level allows further scrutiny of this result. To this end, I employ subsidiary-level data using emission and financial data for reporting subsidiaries. Table 4 investigates treatment effects on subsidiary-level outcomes to test whether these results are consistent with the conjectured mechanism of winner-picking. In particular, I test whether firms appear to protect more emission-intensive subsidiaries following the credit crunch induced by the EBA capital exercise. *Treated* remains as in the baseline and indicates subsidiaries of treated parents. In Columns (1) and (2) the main dependent variable is subsidiary *Ln Total Assets* and the specification includes parent fixed effects as well as subsidiary industry-year and country-year fixed effects and firm controls. Firm controls are averages over the pre-shock period and include Total Assets, Tangibility, and Leverage at the subsidiary level. Column (1) shows a significant decline in subsidiary size following the shock. However, Column (2), which introduces an interaction with the indicator *Dirty Subs* for subsidiaries participating in the EU ETS, shows that this is only the case for clean subsidiaries. This effect is not present for dirty ones as indicated by the positive coefficient for the triple interaction *Treated* $\times$ *Post* $\times$ *Dirty Subs* and the nonsignificant marginal effect.

[Table 4]

Columns (3) and (4) focus on the subsample of dirty subsidiaries and compare the development of dirty subsidiaries of treated firms relative to dirty subsidiaries of control group firms. Due to the limited number of observations the fixed effect structure is relaxed to parent, year, industry, and country fixed effects at the subsidiary level. The results align with the model prediction that in a credit crunch firms protect dirty subsidiaries. Despite the evidence at the consolidated level that the firm faces a significant credit crunch, dirty subsidiaries of treated parents do not develop differently relative to dirty subsidiaries in the control group.

The validity of this exercise rests on the parallel trends assumption. To provide evidence that the treatment and control group firms would have followed the same trends in the absence of treatment, I report the pre-shock average annual percentage changes of relevant characteristics of the firms in these two groups in Table 6. The results of two-tailed t-tests confirm that firms in the two groups develop similarly before treatment with regard to the main variables included in the analysis.

[Table 6]

Figure 2 shows further evidence that the parallel trends assumption holds for the baseline results. The figure displays the baseline specification in dynamic form for the two main dependent variables and reports the yearly treatment coefficients. These, are not significantly different from zero during the pre-shock period. Hence, Table 6 and Figure 2 provide support for the validity of the parallel trends assumption in this sample.

[Figure 2]

Furthermore, as I exploit the EBA capital exercise as an example of a credit crunch, in Table 5 I confirm that exposure to lenders that participated is associated with significant changes in firms' debt levels or borrowing costs. Gropp et al. (2018) show that lenders involved in the EBA exercise significantly reduce corporate lending volumes. Also using Amadeus financial data, they find significant impacts on firm outcomes for non-listed borrowers. In Panel A Columns (1) to (4) I report estimates of treatment effects on debt, equity, leverage, and interest paid ratio for my baseline sample of non-listed firms.

[Table 5]

In Panel B the regression is run on a sample of listed firms. Non-listed firms are less likely to be able to easily substitute to other forms of debt financing compared to listed firms and this is reflected in the results. The impact of the EBA credit crunch is only significant for non-listed firms that experience a significant decline in debt volumes (Column (1)). Equity levels do not increase significantly (Column (2)), while leverage declines (Column (3)). There is no apparent effect on the paid interest ratio, this is however only a rough proxy for interest rate as it is defined as paid interest over total debt. These results are consistent with treated non-listed firms experiencing a tightening in access to financing following the EBA capital exercise. Since listed firms appear to be able to evade real consequences from this shock, in the analysis I focus on non-listed firms.

In Appendix B, I provide further robustness tests. Table B4, shows that the baseline results are not reliant on the specific fixed effect structure by providing several less stringent specifications. I sequentially introduce year, industry-year, and country-year fixed effects as well as ex-ante average firm controls. I also confirm the robustness of the main results with respect to different treatment definitions in Table B5. In Panel A I consider a continuous exposure measure, while in Panel B, I exclude treated firms that only borrow from subsidiaries of lenders that participate in the EBA Exercise. Allowing for different intensities of treatment does not lead to qualitatively different results relative to the baseline.

Overall these results support the predictions for a credit crunch scenario and the proposed impact of winner-picking on firms' environmental performance. Treated firms exposed to increasing financial constraints follow winner-picking incentives and contract funding to the cleaner side of the business while continuing to support the dirtier side. As profitability increases with this adjustment, these results provide further evidence that for this type of firm, the marginal project appears to be clean, as modeled in the theoretical section.

3.4 A Social Preferences Scenario: Sustainable Lending Commitments

In this second part of the empirical analysis, I employ a different natural experiment to test whether the impact of a tightening in credit constraints on firms' outcomes is different when the constraint is a consequence of firms' social costs. To test the social preferences scenario's predictions, firms must face a tightening in credit constraints that is correlated with their emission intensity. This can manifest when a lender makes a public commitment to lend sustainably. As a natural experiment, I exploit banks' commitments to SBTi similarly to Kacperczyk and Peydró (2021).

While arguably both the EBA exercise participation and SBTi commitments may lead to a reduction in access to credit for firms in emission-intensive sectors, firms' adjustments to these two shocks can differ as modeled in the theoretical section. The main difference relative to the EBA exercise, that I aim to exploit in this setting, is the fact that high-emitting firms that are linked to SBTi committed banks are treated because of their dirty status. These firms can then face both winner-picking, as well as constraint-minimization incentives. They may choose to continue to protect their dirty projects, as treated firms did in the credit crunch scenario. However, they might instead prefer to shrink in their dirty side, to reduce the constraint and perhaps attract more and cheaper funding in the future.

This natural experiment differs from the EBA capital exercise along several dimensions, limiting a direct comparison between the two beyond a qualitative one. First, participation in SBTi is voluntary. However, it does not seem that ex-ante more sustainable lenders select into this commitment. Kacperczyk and Peydró (2021) report stakeholder pressure as a main reason for banks' commitments and importantly they do not find that committed banks differ ex-ante in their lending with respect to brown firms relative to banks in their control group. Second, the SBTi targets are not comparable to the 9% core tier 1 ratio target in the EBA exercise. When making a commitment, lenders pledge to design and adhere to a specific, individual, science-based target of portfolio decarbonization. Progress towards the target is then tracked by the Carbon Disclosure

Project (CDP), annual reports, or sustainability reports. Nevertheless, while the commitment to portfolio decarbonization is not binding, progress is tracked and failure to meet and set targets is reported and can lead to a removal from the program, which in turn may lead to reputational damage. A further difference stems from the fact that commitments are staggered across time, with the first ones starting in 2015. A complete list of lender commitments along with commitment year is provided in Appendix Table B3. Due to this, instead of the standard DiD approach used in Section 3.2, I employ a staggered DiD approach following the methodology of Sun and Abraham (2021). It is also important to note that while the two scenarios are tested using the same firms and lending relationships the two analyses are conducted in two separate time periods (2009-2012 for the EBA Exercise and 2013-2019 for SBTi commitments). Moreover, as shown in Appendix Table B3, different relationships lead to treatment in each scenario and the samples are only partially overlapping due to firms in the data set not reporting throughout the sample period. Hence treatment and control firms are not fixed across scenarios. Given all these points, the goal of this analysis is to test the predictions of the model in a social preference scenario and observe whether in this setting firms' adjustments are consistent with the theoretical predictions for winner-picking or constraint-minimization incentives.

SBTi commitments have been shown to cause a reduction in bank funding for firms linked to committed banks. Using a sample of large, international, listed firms, Kacperczyk and Peydró (2021) show that after 2015 high-emitting firms with an SBTi lending relationship experienced a reduction in credit access. The treatment is also associated with a decline in size, no significant impact on emission levels, and an increase in profitability. Using the model predictions in this paper, the results in Kacperczyk and Peydró (2021) are consistent with the winner-picking equilibrium in Proposition 2. As a reaction to the credit constraint, firms in their sample appear to engage in winner-picking: they protect the dirty side of the business and shrink their clean assets.

To test the model prediction in a social preferences scenario, I also exploit firms' exposure to lenders that make an SBTi commitment. While the shock used is the same as in Kacperczyk and Peydró (2021), the following analysis differs along several dimensions and has a different focus. I focus on the mechanisms underpinning firms' adjustments to this credit-constraining shock and furthermore, my data allows investigating within-firm variation and provides a more granular perspective on the multifaceted dynamics at play. The laboratory for the analysis is also an important differentiating factor. This analysis focuses on a sample of smaller, non-listed, and European firms. Non-listed firms are more likely to be reliant on bank financing and therefore could be more sensitive to lenders' commitment decisions. The results using European firms could also differ because of the regulatory environment with regard to environmental regulation and in particular expectations about sustainable transition paths. Already before the first SBTi commitments in 2015, European countries performed relatively better environmentally, compared to other regions of the world.[7] It is possible that in countries with more stringent environmental regulation, the distance in profitability between clean and dirty projects is lower, which could lead to a higher likelihood of a constraint-minimization reaction in this analysis.

In the analysis, I employ a staggered DiD approach following the methodology of Sun and Abraham (2021). This is in contrast with the standard DiD setting in Kacperczyk and Peydró (2021), which considers 2015 as the beginning of the treatment period. A staggered approach can better pinpoint the effect of the staggered commitments and observe the dynamic effect of treatment on relevant firm outcomes. Moreover, the staggered DiD methodology proposed by Sun and Abraham (2021) allows for treatment effect heterogeneity across cohorts, estimates cohort-time specific treatment effects, and delivers weighted average effects of treatment based on cohort shares. This methodology is one of the new proposed tools to deal with bias in standard two-way fixed effects staggered DiD caused by already treated units acting as effective controls.[8]

I estimate the following main regression specification:

$$Y_{ft} = \sum_{l \in \{-3,-2,0,1,2,3\}} \beta_l L^l_{ft} + \zeta_f + \zeta_{it} + \zeta_{lt} + \varepsilon_f. \tag{13}$$

Akin to the credit crunch scenario, firms are treated when the firms' main lender makes an SBTi commitment. The relationship is defined using lending relationships in Amadeus Bankers from 2012, thereby fixing the relationships to the pre-shock period. To avoid the same firm being treated multiple times for multiple lending relationships, firms are considered treated from the first lender commitment. The control cohort is composed of firms whose lenders do not make a commitment within the sample period. Instead

[7] The 2014 Climate Change Performance Index (CCPI) from Germanwatch, lists only European countries among the top 10 best performing countries, while Anglo-American countries, Asian countries, and developing economies rank typically lower. Source: CCPI Results 2014, available at: `https://germanwatch.org/sites/default/files/publication/8600.pdf`

[8] For an extended discussion of the issue and an overview of the proposed new methods see Baker et al. (2022).

of the post-treatment indicator the specification includes event-time indicators Ll_{ft} for three leads and lags around the treatment event. The year before treatment is normalized to zero. The sample period is from 2013 to 2019. In line with the specification in the credit crunch scenario, the regression includes firm, industry-year, and location-year fixed effects. The main dependent variables are ROA and Emission Intensity.

This analysis can also shed light on within-firm reallocation activity. After confirming a significant impact on parent firms' outcomes, subsidiary-level information can be exploited to observe whether there is a differential effect on subsidiaries of treated parents depending on whether these are classified as dirty or clean. This extension can be used to confirm the theoretical predictions in Proposition 2.

3.5 Results: Sustainable Lending Commitments

In this section, I test whether exposure to sustainable lenders' commitments can lead to firm adjustments consistent with the predictions in Proposition 2 of the model. Proposition 2 highlights two potential equilibrium solutions depending on whether winner-picking incentives prevail or there is a switch in the relative ranking of clean and dirty projects making constraint-minimization the utility optimizing adjustment.

The effect of treatment on the main dependent variables *ROA* and *Emission Intensity* is reported in Figure 3 in the top two graphs. The impact of treatment on profitability seems to be short-lived and only present in the treatment year while the impact on emission intensity is not significant. In particular, treated firms present a 0.3 to 0.5 percentage point lower ROA compared to control group firms in the treatment year and the following year. This result deviates from the one observed following the EBA exercise, where treatment led to relatively higher profitability and emission intensity. The bottom two graphs of Figure 3 decompose the effect on emission intensity between the effect on size and emission levels. The estimated effects show that the lack of impact on emission intensity is explained by a relative decline in size and a proportional reduction in emission levels relative to the control group. Differently from the impact on profitability, these effects are persistent. Following a reduction in credit access as a consequence of lenders' sustainable commitments, treated firms do not appear to engage in winner-picking and shrink at the margin, as profitability declines in the short term. However, this result is more consistent with constraint-minimization, although the reduction in emission levels is not sufficiently pronounced to trigger a decline in emission intensity.

[Figure 3]

Observing the impact of treatment on the subsidiaries of treated parents can help shed some light on these first results. Figure 4 reports the dynamic impact of treatment on subsidiary size, conditional on the subsidiary being either clean (in green) or dirty (in red). This specification is estimated at the subsidiary level and includes group-specific relative time indicators for clean and dirty subsidiaries. In contrast, to the EBA exercise results, clean subsidiaries of treated parents are not impacted negatively in this setting. Instead, I find that, in the short term (the treatment year), dirty subsidiaries experience a relative decline in total assets of similar magnitude compared to the parent-level effect (around 4%). Differently from the credit crunch setting where dirty subsidiaries were protected from the decline in access to funding, in this scenario, if there is an effect, it is that dirty subsidiaries shrink relatively to clean ones. This type of adjustment is more aligned with the constraint-minimization equilibrium in Proposition 2.

[Figure 4]

Akin to the exercise in Table 4 Columns (3) and (4), the first two graphs in Figure 5 show the development of dirty subsidiaries of treated parents relatively to control group dirty subsidiaries. Interestingly there is no significant impact of treatment, indicating that dirty subsidiaries of treated parents do not present with relatively lower emission intensity nor declining emissions. In the third graph in the lower part of Figure 5, I show the effect of treatment on *Distance in Ownership*. This variable is equal to one when there is a direct ownership link between the parent and the subsidiary, while it takes higher values for each intermediate relationship between the two. The results indicate that subsidiaries of treated parents are more likely to grow more distant from the parent after treatment, relatively to dirty subsidiaries of control parents. This is consistent with parent companies seeking to distance themselves from the dirty side of their business, perhaps to improve access to credit. This is aligned with the results in Duchin et al. (2023), who find that divested dirty assets are more likely to be sold to firms that have business ties with the seller, indicating a cosmetic redrawing of firm boundaries rather than a real adjustment.

[Figure 5]

The subsidiary-level results, particularly with regard to the size and distance effects, provide corroborating evidence that the treatment triggers adjustments more aligned with constraint-minimization, rather than winner-picking. However, there appears to be a disconnect between the aggregated level effect and the subsidiary adjustments. The baseline results highlighted a persistent decline in size and emissions, while at the subsidiary level, this is not observed. Where this adjustment takes place is pictured in Figure 6. In the left-hand side graph, the main dependent variable is *Ln Emissions* at the parent level, while on the right-hand side, I plot the treatment effect on aggregated emissions across subsidiaries. From this figure, it is clear that treated firms do engage in emission reduction, but they do so at the parent level.

These results are consistent with constraint-minimization being undertaken with the intent to improve access to funding. Treated parents distance themselves from dirty subsidiaries and engage in emission reduction where emissions are more visible to the lender. While these results show a reality more complex than the simple theoretical framework proposed, treated firms' behavior can be considered constraint-minimization aimed at catering to sustainable lenders seeking to green their portfolios.

[Figure 6]

The validity of these results relies on the parallel trends assumption. A standard practice in the literature is to test for evidence of pre-trends using pre-shock coefficients. In the case of traditional staggered DiD, this assumption is problematic as contamination from treatment effects from other periods can bias the estimated coefficients. However, the interaction-weighted estimation proposed by Sun and Abraham (2021) alleviates this concern by correcting for the bias introduced by treatment effect heterogeneity across cohorts improving the reliability of this practice. The pre-treatment coefficients in Figure 3 show no indication of pre-trends and a joint F-test of lead coefficients fails to reject the null that they are jointly zero. Table 7 provides further evidence to support the parallel trends assumption by comparing the development of treated and control group firms across several characteristics. Firms exposed to lenders that make a sustainable commitment do not show significantly different growth trends before treatment with regard to their funding structure, profitability, emission levels, or size relative to the control group of firms that are never treated.

[Table 7]

As in the case of the EBA Exercise, the first-order effect of treatment should be on firms' access to credit. Figure 7 reports the results of estimating the staggered DiD specification in Equation (13) using firms' debt, equity, leverage, and interest ratio as dependent variables. Relatively to the control group, firms linked to lenders that make a commitment experience significantly lower debt levels of around 1%. Following treatment equity levels are not changing significantly, while leverage declines. There is no effect on the interest ratio.

[Figure 7]

In Appendix B I also report the results of further robustness tests. Figure B2 shows that the dynamic treatment effect estimated in the baseline results is not dependent on the specific number of leads and lags chosen. To show this, I extend the event period by an extra lead and lag. The results are consistent with the baseline in Figure 3. In Figure B3, I employ an alternative approach to address the bias in staggered D-i-D estimation and show results are qualitatively aligned with the baseline. For this test, I follow Cengiz et al. (2019) and employ a stacked regression where the fixed effects are event-specific. This delivers average treatment effects that are not biased by treatment effect heterogeneity.

4 Conclusion

This paper investigates the mechanisms behind high-emitting firms' adjustments to tightening financial constraints. A simple theoretical model based on Tirole (2006) shows how firms' incentives can shape these adjustments and their consequences for firms' profitability and emission intensity. The empirical analysis tests the model predictions in two separate scenarios showing the mechanisms proposed can manifest in real-world settings.

High-emitting firms confronted by a tightening in access to funding can face two contrasting incentives. Firms always have an incentive to engage in winner-picking. In this case, they protect the profitable side of their business and reduce funding to the marginal project, leading to an increase in profitability. When the marginal project is clean this adjustment also leads to an increase in emission intensity. However in cases when the tightening in access to credit is caused by the firms' high emitting status, the firm can instead choose to engage in constraint-minimization. In this case, the firm shifts funding to the cleaner side of the business, improving access to funding by improving its environmental performance but reducing its profitability.

In the first scenario of the theoretical model, I mute constraint-minimization incentives by considering a tightening in access to credit that is exogenous to firms' environmental outcomes. In this credit crunch scenario, the firm only adjusts following winner-picking incentives increasing its profitability and emission intensity by decreasing production in the clean marginal project. I test this prediction in the data using firms' exposure to lenders that participate in the EBA capital exercise in a DiD setting over the period 2009 to 2012. Using a sample of non-listed, European firms participating in the EU ETS, I find that firms' adjustments following a credit crunch lead to an increase in profitability and emission intensity. In particular, within-firm analysis shows that clean subsidiaries of treated parents shrink in size, while dirty ones do not, lending support to the theoretical assumption that the clean project is at the margin for this type of firm.

The second scenario considered in the model introduces social preferences to financial intermediaries. This creates a tightening in access to credit for the firm that is directly related to its environmental performance. In this case the firm can adjust by either engaging in winner-picking or in constraint-minimization. This scenario introduces two possible equilibria and there is a threshold between the two. The threshold is linked to the relative profitability of clean and dirty projects and their emission intensity as well as the degree of internalization of firms' social costs by the lender. If the threshold is not reached the firm adjusts following winner-picking incentives and the predictions are as in the credit crunch scenario. If the firm tips towards constraint-minimization instead the model predicts a decline in profitability and emission intensity due to a reduction in production in the dirty more profitable project.

In the empirical analysis, I test whether firms can react differently to a tightening in access to credit when it is driven by lenders' sustainable commitments. To this end, I exploit exposure to lenders' SBTi commitments in a staggered DiD setting over the period 2013 to 2019. In this case, I find that treated firms experience a short-term decline in profitability and no significant change in emission intensity, indicating that firms do not as in the credit crunch scenario, favor the dirty side of the business. Instead, treated firms shrink in size relatively to the control group, while concurrently reducing their emissions in a proportional manner. These reductions are consistent with constraint-minimization behavior. The fact that emission reductions are concentrated at the parent level, where they might better improve access to funding further corroborates this conclusion.

While the empirical part of this work focuses on the impact of access to bank financing on high-emitting firms' environmental outcomes, the theoretical model can be generalized across different scenarios and leaves room for future work to confirm its applicability. This analysis focuses on changes in access to bank financing. Nevertheless, changes in regulation or preferences might also affect other types of investors' behavior leading to similar contractions in funding availability. Moreover, the model is limited to one source of funding, however in the case of multiple funding sources relative costs will determine funding choices and substitution might mitigate these effects. The model is also not specific to emissions and environmental externalities. The predictions may apply to other firm characteristics with a positive relationship with profitability and associated with a negative externality that investors may choose to internalize, for example in social and governance contexts.

This paper contributes to the growing literature on climate finance by providing a structured investigation of the mechanisms that drive within-firm reallocation of funding following a shock to credit constraints in the specific case of high-emitting firms. I show that when facing a tightening in access to credit, high-emitting firms engage in winner-picking and reduce production in their clean marginal projects. However, when the tightening is driven by the firms' dirty status, firms can engage in a constraint-minimization behavior.

References

Acharya, Viral V, Tim Eisert, Christian Eufinger, and Christian Hirsch (Apr. 2018). "Real Effects of the Sovereign Debt Crisis in Europe: Evidence from Syndicated Loans". *The Review of Financial Studies* 31.8, 2855–2896. URL: `https://doi.org/10.1093/rfs/hhy045`.

Allen, Franklin, Adelina Barbalau, and Federica Zeni (2023). "Reducing Carbon using Regulatory and Financial Market Tools". *SSRN Working Paper 4357160*.

Baker, Andrew C, David F Larcker, and Charles CY Wang (2022). "How much should we trust staggered difference-in-differences estimates?" *Journal of Financial Economics* 144.2, 370–395.

Berg, Tobias, Lin Ma, and Daniel Streitz (2023). "Out of sight, out of mind: Divestments and the Global Reallocation of Pollutive Assets". *Available at SSRN 4368113*.

Bolton, Patrick and Marcin T. Kacperczyk (2021). "Do investors care about carbon risk?" *Journal of Financial Economics* 142.2, 517–549.

Ceccarelli, Marco, Stefano Ramelli, and Alexander F. Wagner (2020). "Low-carbon mutual funds". *Swiss Finance Institute Research Paper* No. 19-13.

Cengiz, Doruk, Arindrajit Dube, Attila Lindner, and Ben Zipperer (May 2019). "The Effect of Minimum Wages on Low-Wage Jobs*". *The Quarterly Journal of Economics* 134.3, 1405–1454.

Cestone, Giacinta and Chiara Fumagalli (2005). "The Strategic Impact of Resource Flexibility in Business Groups". *The RAND Journal of Economics* 36.1, 193–214. (Visited on 12/14/2022).

Chava, Sudheer (2014). "Environmental externalities and cost of capital". *Management Science* 60.9, 2223–2247.

De Haas, Ralph, Ralf Martin, Mirabelle Muûls, and Helena Schweiger (2021). "Managerial and financial barriers to the net-zero transition". *CEPR Discussion Paper* No. 15886.

Degryse, Hans, Artashes Karapetyan, and Sudipto Karmakar (2021). "To ask or not to ask? Bank capital requirements and loan collateralization". *Journal of Financial Economics* 142.1, 239–260.

Degryse, Hans, Mike Mariathasan, and Carola Theunisz (2023). "Sharing the Burden Equally? Intra-Group Effects of Bank Capital Requirements". *Working Paper. Available at SSRN 4505260*.

Degryse, Hans, Tarik Roukny, and Joris Tielens (2022). "Asset overhang and technological change". *CEPR Discussion Paper* No. 17507.

Delis, Manthos, Kathrin De Greiff, Maria Iosifidi, and Steven Ongena (2021). "Being stranded with fossil fuel reserves? Climate policy risk and the pricing of bank loans". *Swiss Finance Institute Research Paper Series* No. 18-10.

Döttling, Robin and Magdalena Rola-Janicka (2023). "Too levered for Pigou: carbon pricing, financial constraints, and leverage regulation".

Duchin, Ran, Janet Gao, and Qiping Xu (2023). "Sustainability or greenwashing: Evidence from the asset market for industrial pollution". *SSRN Working Paper 4095885*.

European Commission (2020). "Report on the functioning of the European carbon market". COM(2019) 557 final/2.
Giannetti, Mariassunta and Steven Ongena (2012). ""Lending by example": Direct and indirect effects of foreign banks in emerging markets". *Journal of International Economics* 86.1, 167–180.
Giroud, Xavier and Holger M. Mueller (2019). "Firms' Internal Networks and Local Economic Shocks". *American Economic Review* 109.10, 3617–49.
Goetz, Martin Richard (2019). "Financing conditions and toxic emissions". *SAFE working paper.*
Gropp, Reint, Thomas Mosk, Steven Ongena, and Carlo Wix (Apr. 2018). "Banks Response to Higher Capital Requirements: Evidence from a Quasi-Natural Experiment". *The Review of Financial Studies* 32.1, 266–299.
Gugler, Klaus, Evgeni Peev, and Esther Segalla (2013). "The internal workings of internal capital markets: Cross-country evidence". *Journal of Corporate Finance* 20, 59–73.
Heider, Florian and Roman Inderst (2023). "Environmental Policy with Financial Frictions". *SSRN Working Paper 4000492.*
Holmstrom, Bengt and Jean Tirole (1997). "Financial Intermediation, Loanable Funds, and the Real Sector". *The Quarterly Journal of Economics* 112.3, 663–691. (Visited on 05/11/2023).
Jenkins, Patrick, Ralph Atkins, and Peter Spiegel (2011). "Europe's banks face 9% capital rule". *Financial Times.* URL: `https://www.ft.com/content/e555e7e8-f427-11e0-bdea-00144feab49a`.
Kabbach-de-Castro, Luiz Ricardo, Guilherme Kirch, and Rafael Matta (2022). "Do internal capital markets in business groups mitigate firms' financial constraints?" *Journal of Banking & Finance* 143, 106573.
Kacperczyk, Marcin T. and José-Luis Peydró (2021). "Carbon emissions and the bank-lending channel". *CEPR Discussion Paper* No. 16778.
Krueger, Philipp, Zacharias Sautner, and Laura T. Starks (2020). "The importance of climate risks for institutional investors". *The Review of Financial Studies* 33.3, 1067–1111.
Levine, Ross, Chen Lin, Zigan Wang, and Wensi Xie (2018). "Bank Liquidity, Credit Supply, and the Environment". *NBER Working Paper* 24375.
Mésonnier, Jean-Stéphane and Allen Monks (2015). "Did the EBA capital exercise cause a credit crunch in the euro area?" *International Journal of Central Banking.*
Mueller, Isabella and Eleonora Sfrappini (2022). "Climate Change-Related Regulatory Risk and Bank Lending". *ECB Working Paper Series No. 2670.*
Oehmke, Martin and Marcus M Opp (2023a). "A theory of socially responsible investment". *Working Paper.*
— (2023b). "Green capital requirements". *Working Paper.*
Seltzer, Lee, Laura T. Starks, and Qifei Zhu (2022). "Climate regulatory risks and corporate bonds". *NBER Working Paper* No. 29994.
Stein, Jeremy C. (1997). "Internal Capital Markets and the Competition for Corporate Resources". *The Journal of Finance* 52.1, 111–133.

Sun, Liyang and Sarah Abraham (2021). "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects". *Journal of Econometrics* 225, 175–199.

Tirole, Jean (2006). "The Theory Of Corporate Finance". *Princeton University Press, New York.*

Tables and Figures

Table 1: Summary Statistics

	(1) *Parent Level*	(2) *Dirty Subsidiaries*	(3) *Clean Subsidiaries*	(4) *T-test*
	Mean (SD)	Mean (SD)	Mean (SD)	P-value
Total Assets (Mil US$)	1228.03	90.64	25.54	0.00
	(3502.78)	(77.43)	(47.61)	
Debt (Mil US$)	603.62	46.62	14.80	0.00
	(1850.38)	(40.11)	(26.15)	
Equity (Mil US$)	546.66	42.93	10.32	0.00
	(1756.22)	(41.15)	(23.00)	
ROA	0.03	0.03	0.01	0.02
	(0.03)	(0.08)	(0.11)	
Leverage	0.43	0.55	0.73	0.00
	(0.23)	(0.29)	(1.19)	
Interest Ratio	0.03	0.02	0.02	0.09
	(0.02)	(0.02)	(0.02)	
Tangibility	0.63	0.56	0.38	0.00
	(0.16)	(0.22)	(0.32)	
Emission Intensity (1000 tCO_2/Mil US$)	0.56	3.88		
	(1.90)	(39.01)		
Emissions (1000 tCO_2)	126.57	120.64		
	(266.77)	(361.29)		
Total Emissions (1000 tCO_2)	199.14			
	(725.87)			
% Dirty Subs	0.12			
% Dirty Parent	0.29			
% Treated (EBA)	0.41	0.51	0.50	
% Treated (SBTi)	0.37	0.71	0.79	
N. of Firms (2009-2019)	556	257	3421	
N. of Firms Credit Crunch	241	195	2783	
N. of Firms Social Preferences	478	124	1799	

Note: This table shows summary statistics of relevant firm characteristics at the parent level in Column (1), at the subsidiary level for subsidiaries with installations participating in the EU ETS in Column (2), and for other EEA EFTA Subsidiaries in Column (3). Column (4) reports P-values of two-tailed t-tests between clean and dirty subsidiaries. Variable definitions are in Table B1. All means are constructed over the sample period between 2009 and 2019. All financial variables are winsorized at the 5th and 95th percentiles.

Table 2: Characteristics of dirty subsidiaries

	(1) ROA	(2) Ln Total Assets
Dirty Subs	0.012*	0.886***
	(0.006)	(0.102)
Observations	3166	3166
Parent-Year FE	Yes	Yes
Subs. Industry FE	Yes	Yes
Subs. Country FE	Yes	Yes
Adjusted R^2	0.136	0.579
Clustering	Country	Country

Note: This table reports results of a subsidiary level regression where the main dependent variable is ROA in Column (1) and Ln Total Assets in Column (2). The explanatory variable is *Dirty Subs* which is an indicator equal to one for subsidiaries with installations participating in the EU ETS. Each specification includes parent-year, as well as subsidiary country and industry fixed effects. Standard errors are clustered at country level of the parent firm and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: EBA Exercise treatment effect on parent firms' outcomes

	(1) ROA	(2) Emission Intensity	(3) Ln Total Assets	(4) Ln Emissions
Treated × Post	0.015***	0.290*	-0.042**	0.075
	(0.003)	(0.144)	(0.018)	(0.076)
Observations	735	735	735	735
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.514	0.930	0.973	0.956
Number of firms	241	241	241	241
Clustering	Country	Country	Country	Country

Note: This table reports changes in firms outcomes following the EBA Exercise, as specified in Equation (12). The dependent variable is indicated in the column header. *Treated* assumes a value of one for parent firms whose main lenders participated in the EBA Exercise and zero otherwise. *Post* indicates the period following the announcement of the EBA Exercise. Each specification includes firm, industry-year, as well as country-year fixed effects. Standard errors are clustered at country level of the parent firm and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: EBA Exercise treatment effect on outcomes of subsidiaries of treated firms

	(1) Ln Total Assets	(2) Ln Total Assets	(3) Emission Intensity	(4) Ln Emissions
Treated × Post	-0.120**	-0.122***	-0.081	0.479
	(0.036)	(0.033)	(1.152)	(0.416)
Treated × Post × Dirty Subs		0.107***		
		(0.024)		
Dirty Subs		0.005		
		(0.003)		
Treated × Dirty Subs		-0.006		
		(0.005)		
Post × Dirty Subs		0.064		
		(0.054)		
$\hat{\beta}_1 + \hat{\beta}_2$		-0.015		
		(0.033)		
Observations	3533	3533	133	133
Parent FE	Yes	Yes	Yes	Yes
Industry-Year S FE	Yes	Yes	No	No
Country-Year S FE	Yes	Yes	No	No
Year FE	No	No	Yes	Yes
Industry S FE	No	No	Yes	Yes
Country S FE	No	No	Yes	Yes
Controls S	Yes	Yes	Yes	Yes
Adjusted R^2	0.988	0.988	0.722	0.504
Number of Parents	241	241	37	37
Clustering	Country	Country	Country	Country

Note: This table reports changes in firms outcomes of subsidiaries of treated parents following the EBA Exercise. Specified similarly to Equation (12) with observations at the subsidiary level. The dependent variable is indicated in the column header. *Treated* assumes a value of one for parent firms whose main lenders participated in the EBA Exercise and zero otherwise. *Post* indicates the period following the announcement of the EBA Exercise. In Column (2) I add a further interaction with *Dirty Subs*. This is an indicator for whether the subsidiary is part of the EU ETS in the pre-shock period. The regressions in Columns (3) and (4) are run on the subsample of dirty subsidiaries. Firm controls are averages over the pre-shock period and include Total Assets, Tangibility and Leverage at the subsidiary level and included in all specifications. The specifications in Columns (1) and (2) include parent fixed effects as well as industry-time and country-time fixed effects at the subsidiary level. Due to the limited number of observations in Columns (3) and (4) the fixed effects are relaxed to include parent, subsidiary industry and country as well as year fixed effects. Standard errors are clustered at country level of the parent firm and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: EBA Exercise treatment effect on parent firms' debt outcomes

	(1) Ln Debt	(2) Ln Equity	(3) Leverage	(4) Interest Ratio
Panel A: Non-Listed Firms				
Treated × Post	-0.187**	0.073	-0.025*	0.000
	(0.077)	(0.090)	(0.012)	(0.002)
Observations	735	735	735	570
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.965	0.961	0.898	0.672
Number of firms	241	241	241	189
Clustering	Country	Country	Country	Country
Panel B: Listed Firms				
Treated × Post	-0.018	-0.072	0.034	-0.008
	(0.061)	(0.124)	(0.019)	(0.004)
Observations	438	438	438	328
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.982	0.954	0.901	0.496
Number of firms	127	127	127	98
Clustering	Country	Country	Country	Country

Note: This table reports changes in firms outcomes following the EBA Exercise, as specified in Equation (12).Panel A is estimated on the baseline sample of non listed firms, while Panel B is estimated using listed firms. The dependent variable is indicated in the column header. *Treated* assumes a value of one for parent firms whose main lenders participated in the EBA Exercise and zero otherwise. *Post* indicates the period following the announcement of the EBA Exercise. Each specification includes firm, industry-year, as well as country-year fixed effects. Standard errors are clustered at country level of the parent firm and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Parallel Trends for EBA shock

	(1) *Treated*	(2) *Control*	(3) *P-value*
Δ Emission Intensity	0.57	0.21	0.17
	(2.30)	(1.22)	
Δ Ln Emissions	0.03	0.02	0.76
	(0.25)	(0.19)	
Δ Ln Total Assets	-0.01	-0.00	0.22
	(0.05)	(0.05)	
Δ ROA	0.52	1.93	0.45
	(5.09)	(16.02)	
Δ Ln Debt	-0.00	-0.00	0.97
	(0.13)	(0.06)	
Δ Ln Equity	0.00	0.00	0.97
	(0.04)	(0.05)	
Δ Leverage	0.03	-0.00	0.40
	(0.38)	(0.10)	
Δ Interest Ratio	0.18	0.17	0.95
	(0.66)	(0.40)	
Δ Tangibility	0.03	0.02	0.35
	(0.15)	(0.07)	
N. of Firms	99	142	
% Dirty Subs.	0.12	0.09	
% Dirty Parent	0.19	0.32	

Note: This table compares average ex-ante annual percentage changes in the characteristics of treated (Column(1)) and control group (Column (2)) non-listed firms before the EBA Exercise with standard deviations in parenthesis. The third column tests whether the two groups developed similarly and reports the P-value of two-tailed t-tests. Variables with Δ indicate average annual percentage changes in the pre-shock period (2009-2011). The treated group includes firms whose main lenders participated in the EBA Exercise. % Dirty Subs. indicates the average share of subsidiaries that participate in the EUETS. % Dirty Parent indicates the share of parent firms in the treated or control group that participate directly in the EUETS.

Table 7: Parallel Trends for Social Preferences Scenario

	(1) *Treated*	(2) *Control*	(3) *P-value*
Δ Emission Intensity	0.15	0.17	0.85
	(0.94)	(0.79)	
Δ Ln Emissions	0.02	0.02	0.90
	(0.17)	(0.15)	
Δ Ln Total Assets	-0.01	0.00	0.12
	(0.05)	(0.03)	
Δ ROA	-0.04	-0.07	0.91
	(2.33)	(2.38)	
Δ Ln Debt	-0.01	-0.01	1.00
	(0.15)	(0.10)	
Δ Ln Equity	-0.00	-0.01	0.66
	(0.05)	(0.19)	
Δ Leverage	0.02	0.02	0.99
	(0.50)	(0.37)	
Δ Interest Ratio	0.04	0.09	0.66
	(0.63)	(0.77)	
Δ Tangibility	0.03	0.02	0.53
	(0.12)	(0.10)	
N. of Firms	133	302	
% Dirty Subs.	0.09	0.11	
% Dirty Parent	0.33	0.28	

Note: This table compares average ex-ante annual percentage changes in the characteristics of treated firms in the social preferences scenario (Column(1)) to average annual percentage changes in the control group (Column (2)) with standard deviations in parenthesis. The third column tests whether the two groups developed similarly and reports the P-value of two-tailed t-tests. Δ indicates average annual percentage changes. The treated group includes firms whose main lenders made an SBTi commitment in the sample period (2013-2019). % Dirty Subs. indicates the average share of subsidiaries that participate in the EUETS. % Dirty Parent indicates the share of parent firms in the treated or control group that participate directly in the EUETS.

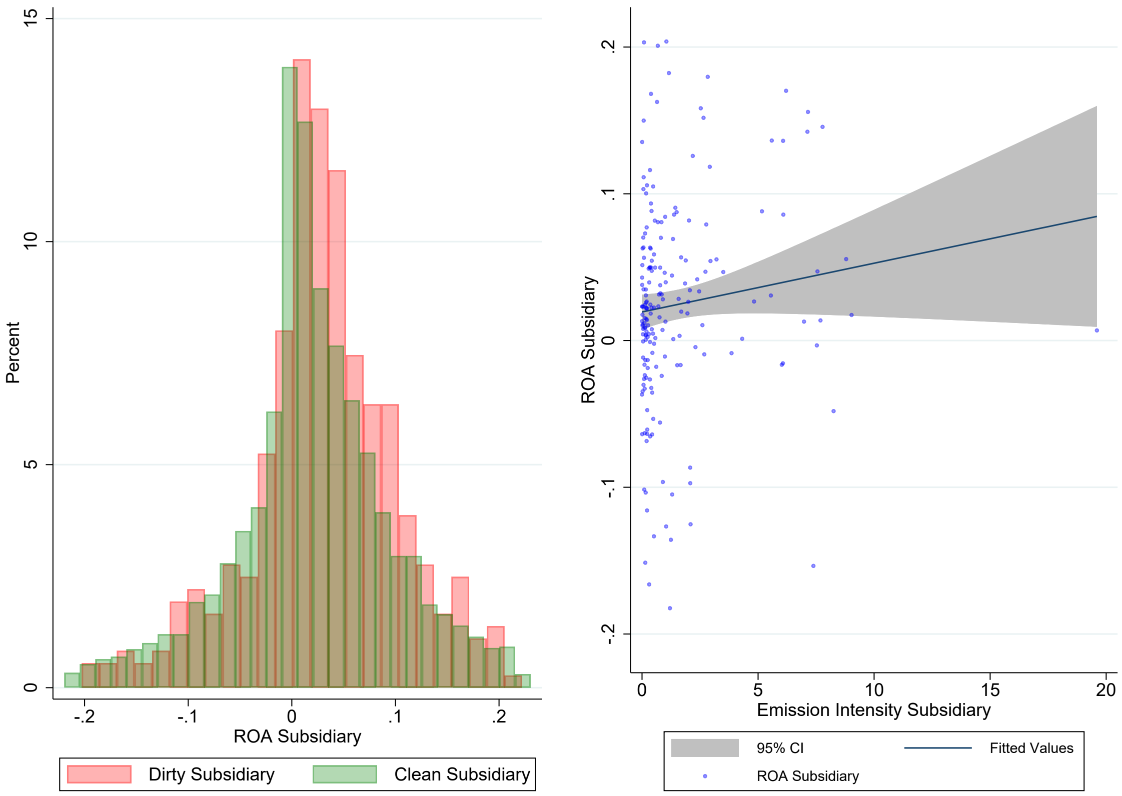

Figure 1: Correlation between Emission Intensity and Profitability

Note: The two graphs depict the distribution of ROA conditional on the subsidiary being dirty or clean (left) and the correlation between emission intensity and ROA at the subsidiary level (right). Both figures show data at the subsidiary level over the time period 2009-2019. The left side figure shows the distribution in percent for each bin. The right side figure includes a fitted linear estimation of the relationship between ROA and Emission Intensity at the subsidiary level surrounded by 95% confidence bands.

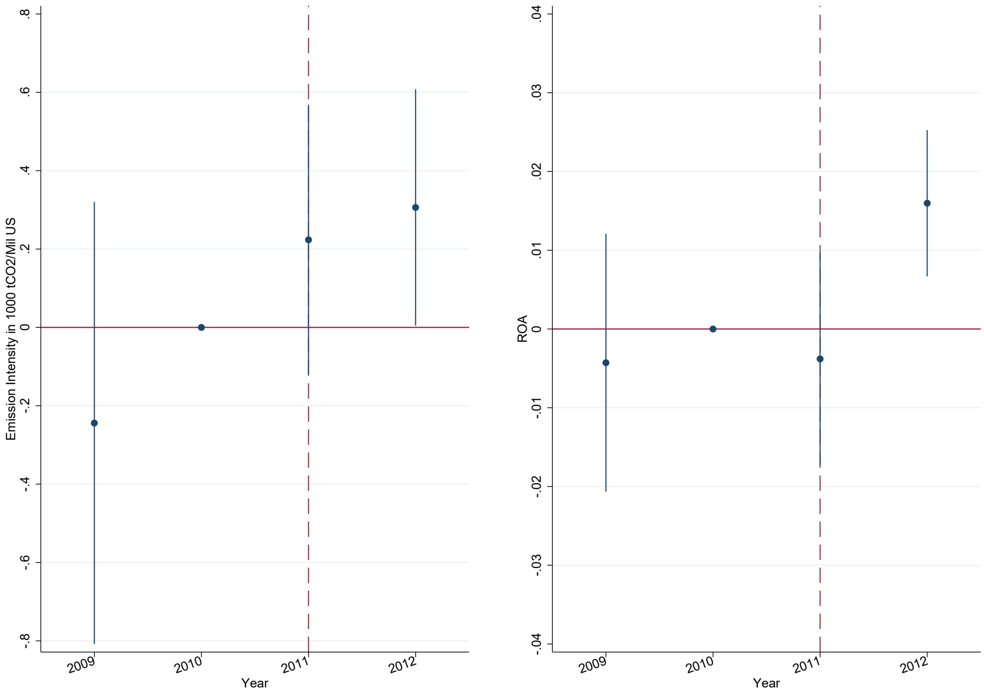

Figure 2: Event study in dynamic form

Note: The graphs depict the baseline EBA event study in dynamic form for the two main variables in the analysis. The dependent variable is *Emission Intensity* on the left and *ROA* on the right. As in Equation (12), each specification includes firm, industry-year, as well as country-year fixed effects. Standard errors are clustered at country level. The specification substitutes *Post* with yearly indicators. Coefficient estimates are surrounded by 95% confidence bands.

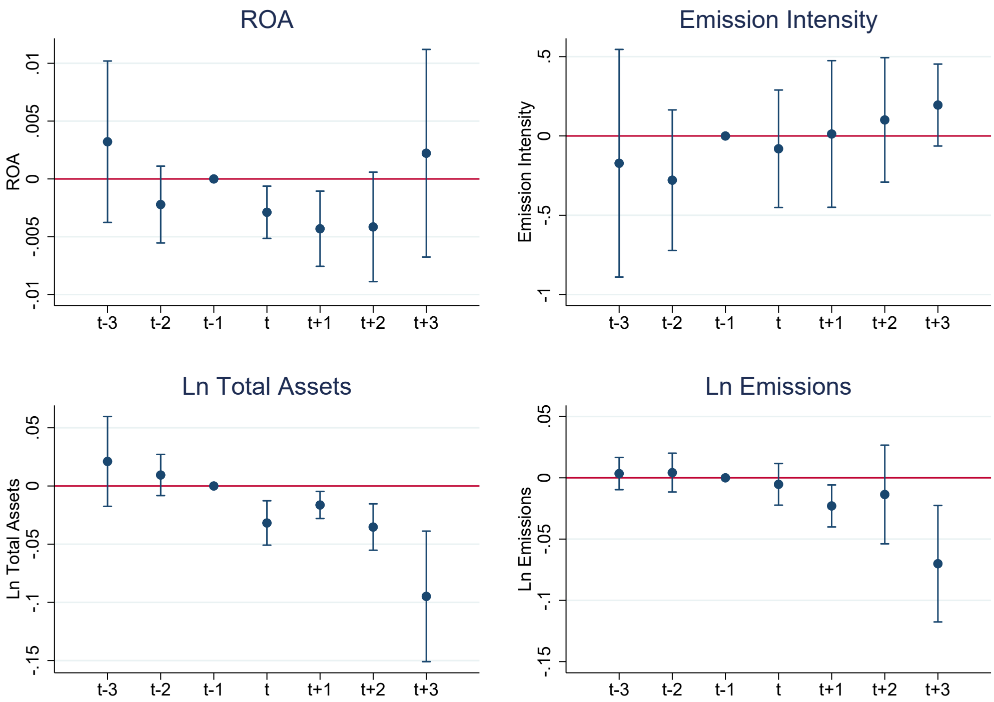

Figure 3: Social Preferences: Baseline

Note: The graphs depict the baseline social preferences event study for the two main variables in the analysis in the top graphs (ROA and Emission Intensity) as well as the decomposition of the effect on emission intensity in the bottom two graphs (Ln Total Assets and Ln Emissions). As in Equation (13), each specification includes firm, industry-year, as well as country-year fixed effects. Standard errors are clustered at country level. Coefficient estimates are surrounded by 95% confidence bands.

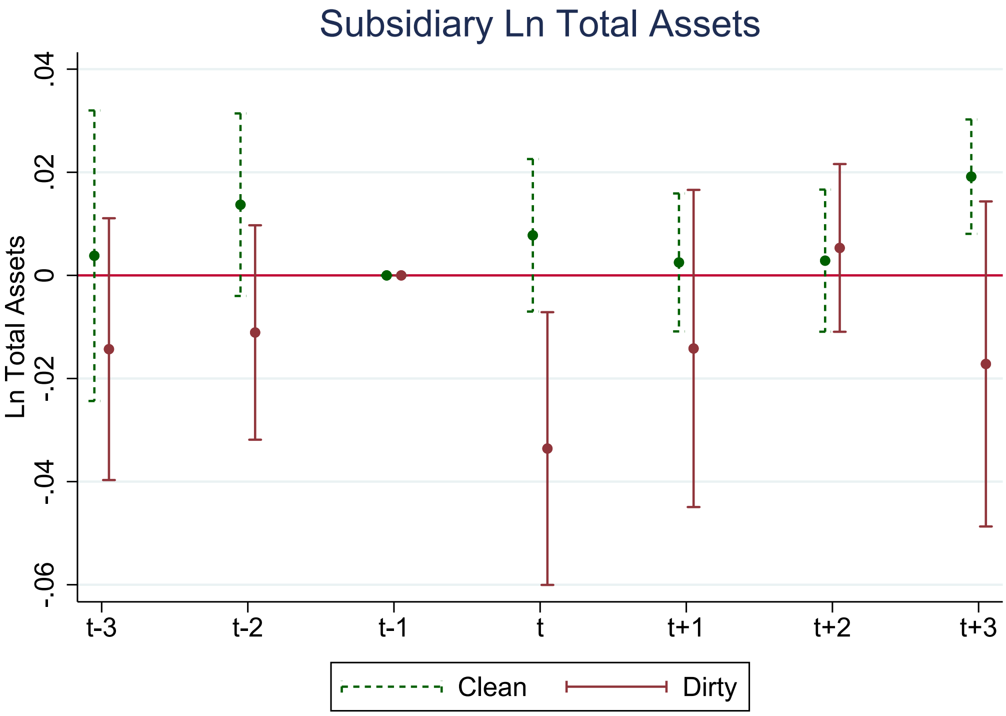

Figure 4: Social Preferences: Subsidiary Size Effects

Note: The graph depicts the estimated coefficients of the social preferences event study at the subsidiary level. In particular the graph depicts the effect of treatment on Ln Total Assets conditional on the subsidiary being either clean or dirty. The following specification is estimated:

$$Y_{fts} = \sum_{l \in \{-3,-2,0,1,2,3\}} \beta_l L^l_{fts,clean} + \beta_l L^l_{fts,dirty} + \zeta_f + \zeta_s + \zeta_t + \varepsilon_f.$$

Each specification includes parent, year, and subsidiary fixed effects. Standard errors are clustered at the country level of the parent firm. Coefficient estimates are surrounded by 95% confidence bands.

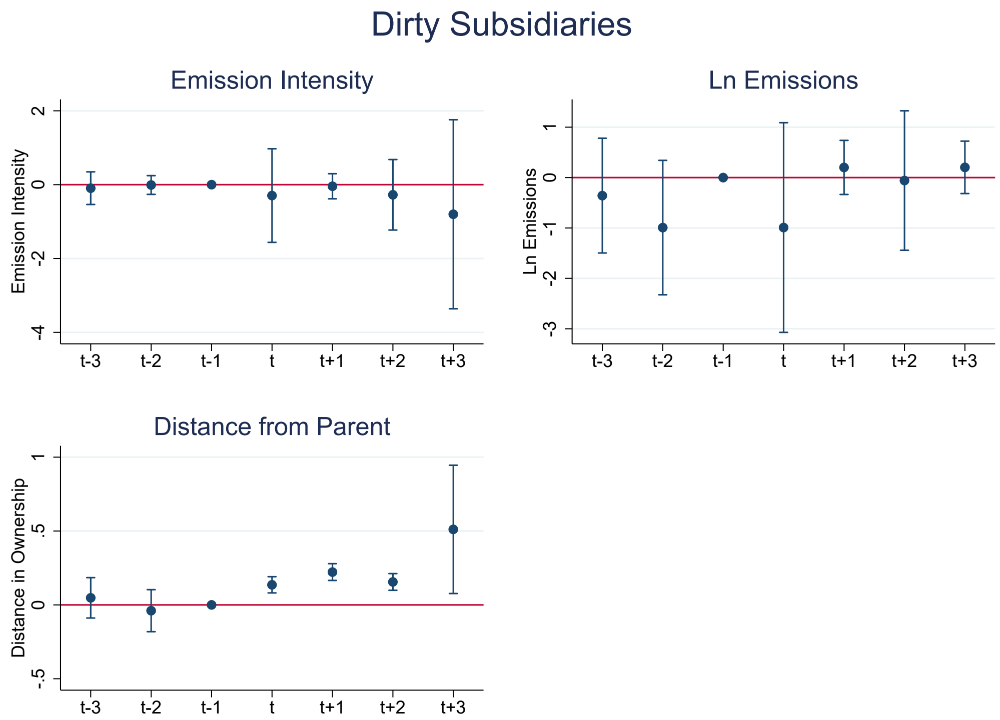

Figure 5: Social Preferences: Dirty Subsidiaries Outcomes

Note: The graph depicts the estimated coefficients of the social preferences event study at the subsidiary level. The two top graphs depict the effect of treatment on Emission Intensity and Ln Emissions of dirty subsidiaries. The lower graph shows the effect of treatment on Distance in Ownership, where a distance of 1 is a direct ownership relation, and two or more indicates the existence of intermediate subsidiaries. Each specification includes parent, subsidiary and year fixed effects. Standard errors are clustered at the country level of the parent firm. Coefficient estimates are surrounded by 95% confidence bands.

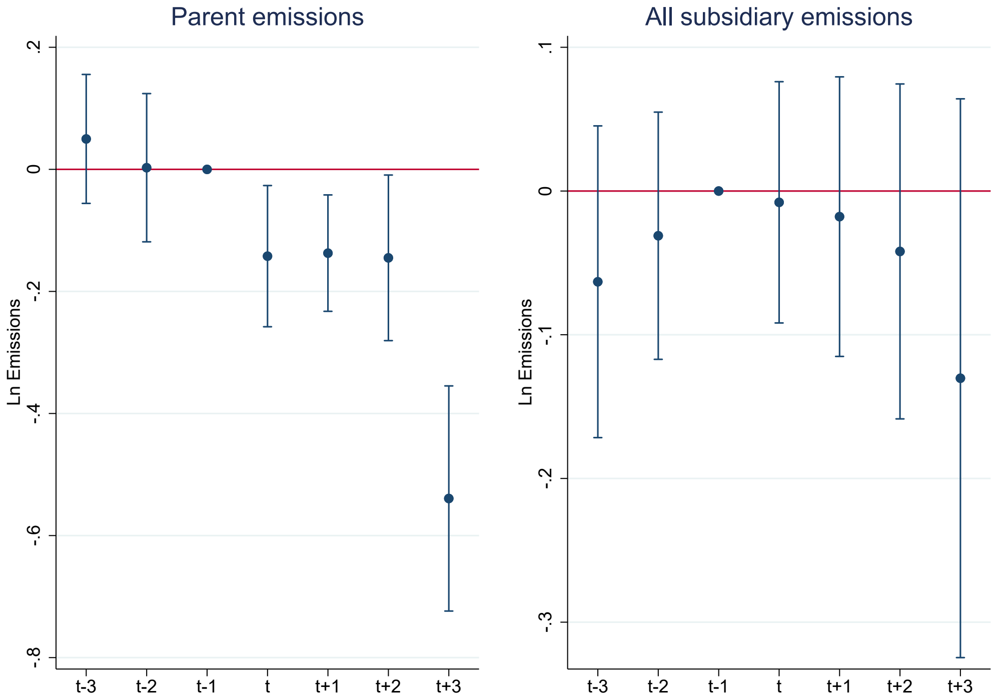

Figure 6: Social Preferences: Where are the emission reductions?

Note: The graphs depict the impact of the social preferences event study on treated firms' emissions at the parent level (left) and aggregated for all subsidiaries (right). As in Equation (13), each specification includes firm, industry-year, as well as country-year fixed effects. Standard errors are clustered at the country of the parent level. Coefficient estimates are surrounded by 95% confidence bands.

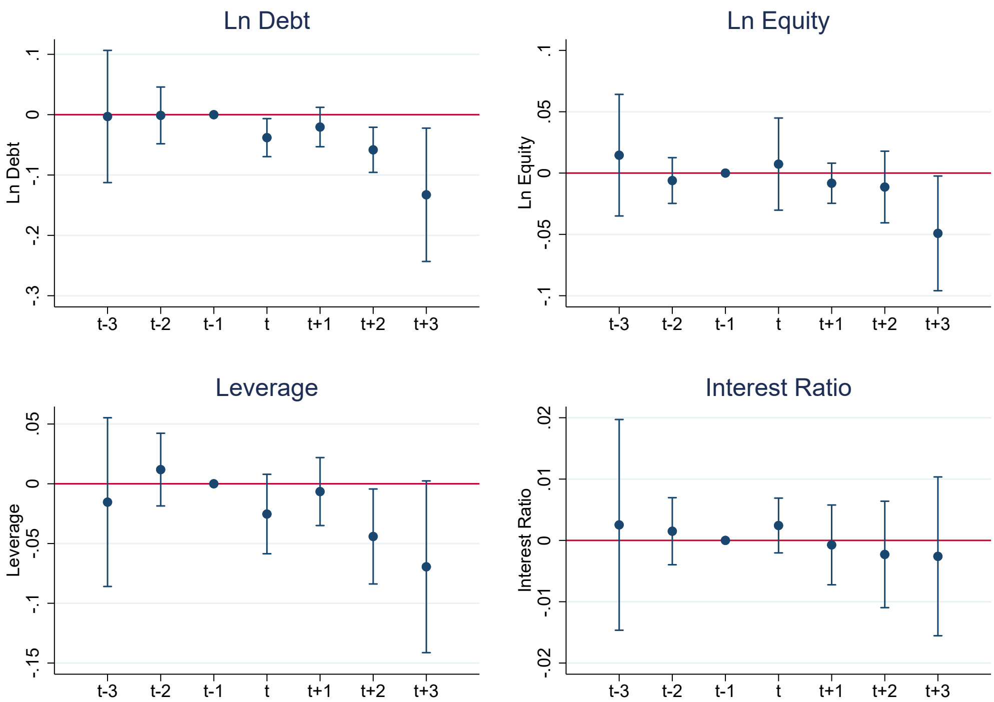

Figure 7: Social Preferences: Lending Outcomes

Note: The graphs depict the impact of the social preferences event study for on treated firms' funding: Ln Debt, Ln Equity, Leverage, Interest Ratio. As in Equation (13), each specification includes firm, industry-year, as well as country-year fixed effects. Standard errors are clustered at the country of the parent level. Coefficient estimates are surrounded by 95% confidence bands.

Appendices

A Proofs from the model and other extensions

A.1 Baseline utility maximization:

The entrepreneur's initial utility maximization program is as described in Equation 19

Lemma A.1 *The entrepreneur always prefers to produce in project D over project C for $K_d < \bar{K}$.*

Proof: Consider the case an individual project (either C or D). The entrepreneurs' problem becomes:

$$\begin{aligned} \max_{R_e,K} \quad & pR_e - A \\ \text{subject to} \quad & IC1: \; R_e \geq \frac{BK}{\Delta p} \\ & IR: \; p(RK - R_e) \geq Kk - A \end{aligned}$$

Writing the Lagrangian for the above program and setting the FOCs equal to 0 delivers:

$$\mathcal{L} = pR_e - A + \lambda \left[R_e - \frac{BK}{\Delta p} \right] + \gamma \left[p(RK - R_e) - Kk + A \right]$$

$$\frac{\delta \mathcal{L}}{\delta R_e} = p + \lambda - \gamma p = 0$$
$$\frac{\delta \mathcal{L}}{\delta K} = -\lambda \frac{B}{\Delta p} + \gamma (pR - k) = 0$$

The first FOC is only satisfied if $\gamma \geq 1$ and $\lambda \geq 0$. The second FOC implies that λ must be strictly positive as $pR > k$ for $K \leq \bar{K}$. As long as $K \leq \bar{K}$, both constraints will bind in equilibrium and the entrepreneur produces:

$$K = \frac{A}{\frac{pB}{\Delta p} + k - pR}$$

From the second constraint, $pR_e = pRK - Kk + A$. Hence the entrepreneur's utility is equal to the total surplus from the project:

$$U_e = K(pR - k)$$

Considering that $k_c > k_d$, for $K \leq \bar{K}$: $U_e^d > U_e^c$.
Since the marginal utility from producing in D is always higher than in C for $K \leq \bar{K}$, the entrepreneur will always produce $\bar{K}$ in D if she has enough own assets to do so.

Assumption 2 ensures this is the case in the baseline. Using $a_d = \bar{K} \left(\frac{pB}{\Delta p} + k_d - pR \right)$ and $pR_e^d = pR\bar{K} - \bar{K}k_d + a_d$, the entrepreneur's initial problem can be simplified to:

$$\begin{aligned}
\max_{R_e^c, K_c} \quad & \bar{K}(pR - k_d) + pR_e^c - a_c \\
\text{subject to} \quad & IC1: \; R_e^c \geq \frac{BK_c}{\Delta p}, \\
& IR1: \; p(RK_c - R_e^c) \geq K_c k_c - a_c
\end{aligned}$$

Solving as in the proof of Lemma A.1, delivers the equilibrium production in the clean project K_c^* as in Equation 6.

A.2 Credit Crunch utility maximization

Introducing r_b in the lender's IR constraints changes the initial entrepreneur's utility maximization to:

$$\begin{aligned}
\max_{R_e^c, R_e^d, K_c, K_d} \quad & pR_e^c + pR_e^d - A \\
& IC1: \; pR_e^c \geq (p - \Delta p)(R_e^c) + BK_c, \\
& IC2: \; pR_e^d \geq (p - \Delta p)(R_e^d) + BK_d, \\
& IC3: \; p(R_e^c + R_e^d) \geq (p - \Delta p)(R_e^c + R_b^d) + B(K_c + K_d), \\
& IR1: \; p(RK_c - R_e^c) \geq (K_c k_c - a_c)(1 + r_b) \\
& IR2: \; p(RK_d - R_e^d) \geq (K_d k_d - a_d)(1 + r_b) \\
& IR3: \; p(RK_c - R_e^c) + p(RK_d - R_e^d) \geq (K_c k_c + K_d k_d - A)(1 + r_b)
\end{aligned}$$

Lemma A.1 continues to apply in this scenario although the proof should be adjusted to include the tighter lender's participation constraint. Producing in D continues to be preferable than in C for $K_d < \bar{K}$. However, in the credit crunch scenario, the entrepreneurs' utility from optimal production in D is lower than in the baseline as capital scarcity allows the lender to capture a share of the project surplus: $U_{e,max}^{d,CC} = \bar{K}(pR - k_d) - (\bar{K}k_d - a_d)r_b$. Moreover, the entrepreneur will employ a higher share of own funds to produce $\bar{K}$ in D:

$$\begin{aligned}
a_d &< a_d^{CC} \\
\bar{K}\left(\frac{pB}{\Delta p} + k_d - pR\right) &< \frac{\bar{K}\left(\frac{pB}{\Delta p} + k_d(1 + r_b) - pR\right)}{1 + r_b} \\
r_b \bar{K}\left(\frac{pB}{\Delta p} - pR\right) &< 0
\end{aligned}$$

This is true as $\frac{pB}{\Delta p} - pR < 0$. This follows from Assumption 2 which can be rearranged to show that the difference is between two negative values:

$$-k_j < \frac{pB}{\Delta p} - pR < -\frac{p}{\Delta p}(pR - k_t).$$

Since Lemma A.1 applies, the original problem can be simplified similarly to the baseline scenario. Differently from the baseline, the entrepreneur has a lower amount of own funds left after producing the optimal amount in D (i.e. $a_c^{CC} < a_c$) and maximizes utility subject to a stricter IR1 constraint:

$$\begin{aligned}
\max_{R_e^c, K_c} \quad & U_{e,max}^{d,CC} + pR_e^c - a_c^{CC} \\
\text{subject to} \quad & IC1: \; R_e^c \geq \frac{BK_c}{\Delta p}, \\
& IR1: \; p(RK_c - R_e^c) \geq (K_c k_c - a_c)(1 + r_b)
\end{aligned}$$

Writing the Lagrangian for the above program and setting the FOCs equal to 0 delivers:

$$\mathcal{L} = U_{e,max}^{d,CC} + pR_e - a_c^{CC} + \lambda \left[R_e - \frac{BK_c}{\Delta p} \right] + \gamma \left[p(RK_c - R_e) - K_c k_c + A - r_b(K_c k_c - A) \right]$$

$$\begin{aligned}
\frac{\delta \mathcal{L}}{\delta R_e} &= p + \lambda - \gamma p = 0 \\
\frac{\delta \mathcal{L}}{\delta K_c} &= -\lambda \frac{B}{\Delta p} + \gamma(pR - k_c - r_b k_c) = 0
\end{aligned}$$

The first FOC is only satisfied if $\gamma \geq 1$ and $\lambda \geq 0$. The second FOC implies that λ must be strictly positive as $pR > k$ and $r_b < \frac{\pi_c}{k_c}$ for $K_c \leq \bar{K}$. Both constraints will bind in equilibrium and the entrepreneur produces:

$$K_c^{CC} = \frac{a_c^{CC}(1 + r_b)}{\frac{pB}{\Delta p} + k_c(1 + r_b) - pR}$$

This is smaller than the baseline production level in C, as:

$$\begin{aligned}
K_c &> K_c^{CC} \\
\frac{a_c}{\frac{pB}{\Delta p} + k_c - pR} &> \frac{a_c^{CC}(1 + r_b)}{\frac{pB}{\Delta p} + k_c(1 + r_b) - pR} \\
\frac{a_c}{\frac{pB}{\Delta p} + k_c - pR} &> \frac{(a_c + r_b \bar{K}(\frac{pB}{\Delta p} - pR))(1 + r_b)}{\frac{pB}{\Delta p} + k_c(1 + r_b) - pR} \\
0 &> (\frac{pB}{\Delta p} - pR)(r_b a_c + (1 + r_b) r_b \bar{K}(\frac{pB}{\Delta p} + k_c - pR))
\end{aligned}$$

The last inequality is satisfied since $\frac{pB}{\Delta p} - pR < 0$ (shown above) while the second term is positive. Intuitively the production in C shrinks because in a credit crunch borrowing becomes more expensive for the clean as well as the dirty project.

A.3 Social preferences scenario: threshold and utility maximization

Introducing social preferences in the lender's IR constraints changes the initial entrepreneur's utility maximization to:

$$\begin{aligned}
\max_{R_e^c, R_e^d, K_c, K_d} \quad & pR_e^c + pR_e^d - A \\
& IC1: \; pR_e^c \geq (p - \Delta p)(R_e^c) + BK_c, \\
& IC2: \; pR_e^d \geq (p - \Delta p)(R_e^d) + BK_d, \\
& IC3: \; p(R_e^c + R_e^d) \geq (p - \Delta p)(R_e^c + R_b^d) + B(K_c + K_d), \\
& IR1: \; p(RK_c - R_e^c) \geq K_c k_c - a_c + \gamma\theta_c K_c \\
& IR2: \; p(RK_d - R_e^d) \geq K_d k_d - a_d + \gamma\theta_d K_d \\
& IR3: \; p(RK_c - R_e^c) + p(RK_d - R_e^d) \geq K_c k_c + K_d k_d - A + \gamma\theta_c K_c + \gamma\theta_d K_d
\end{aligned}$$

Lemma A.1 no longer necessarily applies as the tightening in lender participation constraint is now stricter for the project with higher social costs. This can lead to a shift in the relative ranking of the two projects if the higher funding requirements of the dirty projects outweigh the benefits of their higher profitability.

To observe whether banks' social preferences lead the entrepreneur to prefer producing in project C until $\bar{K}$ before beginning production in project D it is sufficient to compare the entrepreneur's utility for each project $j \in C, D$:

$$\begin{aligned}
\max_{R_e, K_j} \quad & pR_e - A \\
\text{subject to} \quad & IC3: \; R_e \geq \frac{BK_j}{\Delta p} \\
& IR: \; p(RK_j - R_e) \geq K_j k_j - A + \gamma\theta_j K_j
\end{aligned}$$

Under project finance, the entrepreneur chooses to produce quantity K_j^{SP}:

$$K_j^{SP} = \frac{A}{k_j + \frac{pB}{\Delta p} + \gamma\theta_j - pR}$$

Akin to the credit crunch scenario, the lender's preference allows it to capture a share of the total surplus of the project equal to the share of internalized social costs, and the entrepreneurs' utility is reduced to $U_e^j = K_j(pR - k_j - \gamma\theta_j)$. Effectively, the entrepreneur internalizes the social preferences of the intermediaries. Now the entrepreneur will choose to produce in C over D when the marginal utility of producing in C is higher than in D: $pR - k_c - \gamma\theta_c > pR - k_d - \gamma\theta_d$. This delivers a threshold γ^*:

$$\gamma^* = \frac{k_c - k_d}{\theta_d - \theta_c}$$

When the share of internalized social costs is larger than γ^* the relative ranking of the two projects inverts compared to the baseline and the clean project delivers a higher marginal utility compared to the dirty one for $K_c \leq \bar{K}$. In this case, the entrepreneur produces $\bar{K}$ in C and then chooses the level of production in D that maximizes her utility. If the threshold is not reached ($\gamma \leq \gamma^*$) the baseline ranking remains unchanged and the entrepreneur produces $\bar{K}$ in D and then chooses the level of production in C that maximizes her utility. Either way, given the production $\bar{K}$ in project i (which delivers utility $U_{e,max}^i = \bar{K}(pR - k_i - \gamma\theta_i)$ and requires $a_i^{SP} = \bar{K}(k_c + \frac{pB}{\Delta p} + \gamma\theta_i - pR)$), the entrepreneur chooses the level of production K_j^{SC} in the other project j using her remaining assets a_j^{SP}. She maximizes her utility using the following simplified program:

$$
\begin{aligned}
\max_{R_e,K_j} \quad & U^i_{e,max} + pR^j_e - a^{SP}_j \\
\text{subject to} \quad & IC3:\ R_e \geq \frac{BK_j}{\Delta p} \\
& IR:\ p(RK_j - R_e) \geq K_j k_j - a^{SP}_j + \gamma\theta_j K_j
\end{aligned}
$$

Solving delivers the equilibrium production K^{SP}_j:

$$K^{SP}_j = \frac{a^{SP}_j}{\frac{pB}{\Delta p} + k_j + \gamma\theta_j - pR}$$

When the threshold is not reached, the entrepreneur produces K^{SP}_c in the clean project. This is a reduction compared to the baseline production K^*_c as:

$$
\begin{aligned}
K_c &> K^{SP}_c \\
\frac{a_c}{\frac{pB}{\Delta p} + k_c - pR} &> \frac{a^{SP}_c}{\frac{pB}{\Delta p} + k_c + \gamma\theta_c - pR} \\
\frac{a_c}{\frac{pB}{\Delta p} + k_c - pR} &> \frac{a_c - \gamma\theta_d\bar{K}}{\frac{pB}{\Delta p} + k_c + \gamma\theta_c - pR}
\end{aligned}
$$

The inequality holds as the right-hand side fraction has a smaller nominator and larger denominator.

When the threshold is reached the entrepreneur produces K^{SP}_d in the dirty project which is lower than the baseline production $\bar{K}$:

$$
\begin{aligned}
\bar{K} &> K^{SP}_d \\
\bar{K} &> \frac{a^{SP}_d}{\frac{pB}{\Delta p} + k_d + \gamma\theta_d - pR} \\
\bar{K}(\frac{pB}{\Delta p} + k_d + \gamma\theta_d - pR) &> A - \bar{K}(\frac{pB}{\Delta p} + k_c - pR) - \gamma\theta_c\bar{K} \\
\bar{K}(\frac{pB}{\Delta p} + k_d + \gamma\theta_d - pR) + \bar{K}(\frac{pB}{\Delta p} + k_c + \gamma\theta_c - pR) > A &
\end{aligned}
$$

This holds due to Assumption 2 which ensures the entrepreneur is credit-constrained already in the baseline.

A.4 The model with cross pledging

All the basic components of the model are as in the baseline. In this extension to obtain finance the entrepreneur can cross-pledge within the firm: i.e. pledge the income of one project as collateral for the other. In a setting with co-pledging $\rho = \frac{p}{2p-\Delta p} \in (\frac{1}{2}, 1)$ is a measure of economies of diversification between projects.
This leads to small changes in Assumptions 1 and 2:

Assumption 1 with cross pledging: *For each project j per unit of capital:*

$$(pR - k_j) < \rho\frac{pB}{\Delta p} < pR - \frac{p}{\Delta p}(pR - k_t)$$

Assumption 2 with cross pledging:: *The entrepreneur's initial assets A are such that:*

$$k_d\bar{K} - p\bar{K}(R - \frac{\rho B}{\Delta p}) < A < k_c\bar{K} + k_d\bar{K} - 2p\bar{K}(R - \frac{\rho B}{\Delta p})$$

Given that marginal return is higher for project D for lower levels of A the entrepreneur will only produce in project D.[9] Furthermore, the second inequality ensures that the entrepreneur cannot finance both projects with her own assets up to $\bar{K}$ ensuring access to external finance is always needed.

The borrowing contract under cross pledging: Under high effort, the entrepreneur can expect a payoff of R_2 if both projects succeed. Given the projects are independent, this outcome has a likelihood p^2. With likelihood $2p(1-p)$ only one projects succeeds (payoff R_1), while with likelihood $(1-p)^2$ neither project succeeds and the payoff is R_0. To maintain tractability the payoff scheme for the entrepreneur is (R_2, R_1, R_0) with $R_2 > 0$ and $R_1 = R_0 = 0$, i.e. she obtains a positive payoff only in case both projects succeed. It can be shown that there is no strictly better incentive scheme.[10]

Baseline equilibrium The entrepreneur will always prefer to produce in project D up to $\bar{K}$ before initiating production in project C as the dirty project has a higher marginal profit (as in the version without cross-pledging). Assumption 2 ensures that the entrepreneur has enough own assets A to produce a positive amount in the clean project. Hence, she maximizes her utility by deciding the optimal production level in C subject to her own incentive compatibility (IC) constraints and the lenders' individual rationality (IR) constraint:

$$\begin{aligned}
\max_{R_2,K_c} \quad & p^2 R_2 - A \\
\text{subject to} \quad & IC1: \; p^2 R_2 \geq p(p-\Delta p)R_2 + B\bar{K}, \\
& IC2: \; p^2 R_2 \geq p(p-\Delta p)R_2 + BK_c, \\
& IC3: \; p^2 R_2 \geq (p-\Delta p)^2 R_2 + B(K_c + \bar{K}), \\
& IR: \; pR(\bar{K} + K_c) - p^2 R_2 \geq K_c k_c + \bar{K} k_d - A
\end{aligned}$$

The first two incentive compatibility constraints ensure that the entrepreneur does not choose to shirk in either project (IC1, IC2), while the third constraint ensures that she does not in both (IC3). IC3 is a more stringent condition than IC2 and IC1, therefore the first two are satisfied when the third is. The IR constraint ensures that the expected total return on investment minus the payoff for the borrower is equal to or larger than borrowed funds, that is capital expenditures not funded with the invested capital of the borrower.

[9] In the baseline setting it is always the case as marginal profits in project D are higher in this production range and the entrepreneurs' utility only depends on financial profits. When $A < k_d\bar{K} - p(R - \frac{\rho B}{\Delta p})$ the entrepreneur can only pledge profits from project D to obtain financing. In this interval of A values, the entrepreneur produces in project D $K_d < \bar{K}$ obtaining external finance by pledging only profits from project D. When $k_d\bar{K} - p(R - \frac{\rho B}{\Delta p}) < A < k_d\bar{K} - p\bar{K}(R - \frac{B}{\Delta p})$, the entrepreneur could choose to only use project finance to produce in D, but co-pledging allows her to obtain more financing and produce more. As she obtains the total surplus from her projects (due to perfect competition on the lending side) she will always choose co-pledging over project finance.

[10] For any incentive scheme with positive payoffs in R_1 and R_0 that satisfies the three incentive compatibility constraints there exists an R_2 that provides the same expected payoff.

Rewriting the IC constraints shows that the first two ICs are satisfied if the third one is.

$$\begin{aligned} IC1: &\quad R_2 p\Delta p \geq B\bar{K} \\ IC2: &\quad R_2 p\Delta p \geq BK_c \\ IC3: &\quad R_2\Delta p(2p-\Delta p) \geq B\bar{K} + BK_c \end{aligned}$$

From IC1 and IC2:

$$2R_2 p\Delta p \geq B\bar{K} + BK_c$$

It follows that IC3 is a more stringent condition than IC2 and IC1 since:

$$R_2\Delta p(2p-\Delta p) < 2R_2 p\Delta p.$$

Hence the entrepreneur's choice is only determined by IC3. The entrepreneur's choice then be rewritten as:

$$\begin{aligned} \max_{R_2, K_c} &\qquad p^2 R_2 - A \\ \text{subject to} &\qquad IC3:\ R_2 \geq \frac{B(K_c+\bar{K})}{\Delta p(2p-\Delta p)} \\ &\qquad IR:\ pR(\bar{K}+K_c) - p^2R_2 \geq K_c k_c + \bar{K}k_d - A \end{aligned}$$

Writing the Lagrangian for the above program and setting the FOCs equal to 0 delivers:

$$\begin{aligned} \mathcal{L} = p^2R_2 - A + \lambda\left[R_2 - \frac{B(K_c+\bar{K})}{\Delta p(2p-\Delta p)}\right] + \mu\left[pR(\bar{K}+K_c) - p^2R_2 - K_ck_c - \bar{K}k_d + A\right] \\ \frac{\delta\mathcal{L}}{\delta R_2} = p^2 + \lambda - \mu p^2 = 0 \\ \frac{\delta\mathcal{L}}{\delta K_c} = -\lambda\frac{B}{\Delta p(2p-\Delta p)} + \mu pR - \mu k_c = 0 \\ \frac{\delta\mathcal{L}}{\delta\lambda} = R_2 - \frac{B(K_c+\bar{K})}{\Delta p(2p-\Delta p)} = 0 \\ \frac{\delta\mathcal{L}}{\delta\mu} = pR(\bar{K}+K_c) - p^2R_2 - K_ck_c - \bar{K}k_d + A = 0 \end{aligned}$$

First, since $\lambda, \mu \geq 0$, the first condition is only satisfied if $\mu \geq 1$ and $\lambda \geq 0$. Second, the second condition implies that λ must be positive as $pR > k_c$ for $K_c \leq \bar{K}$. Meaning both the IR constraint and the IC constraint must bind. It follows that:

$$K_c^* = \frac{A - \bar{K}\left(\frac{\rho p B}{\Delta p} + k_d - pR\right)}{\frac{\rho p B}{\Delta p} + k_c - pR}$$

The ability to cross pledge mitigates the negative impact of agency costs allowing the entrepreneur to access more funding compared to single project finance.

Credit crunch Scenario The first extension introduces a credit crunch scenario where the firm experiences a decrease in access to credit which is not caused by its own social costs. This is modeled as before, only with cross pledging the IR constraint becomes:

$$IR:\ pR(\bar{K}+K_c) - p^2R_2 \geq (K_ck_c + \bar{K}k_d - A)(1+r_b)$$

Assuming as in the paper that $r_b < \frac{\pi_c}{k_c}$ both constraints bind and the entrepreneur produces a positive amount in the clean project despite the credit crunch. The credit crunch equilibrium K_c^{cc} however decreases to:

$$K_c^{cc} = \frac{A(1+r_b) - \bar{K}\left(\frac{\rho p B}{\Delta p} + k_d(1+r_b) - pR\right)}{\frac{\rho p B}{\Delta p} + k_c(1+r_b) - pR}$$

This is smaller than the baseline K_c^*. Hence, also with cross pledging, the more credit-constrained lenders are the more the entrepreneur shrinks its production in project C. A credit crunch in this model decreases the firm's overall production level but increases its average profitability and the average social costs per unit produced. As stipulated in Proposition 1 in the main model.

Social Preferences Scenario I now introduce socially conscious intermediaries in the setting with cross-pledging. As in the paper, banks now internalize social costs θ_c and θ_d with intensity γ, where $0 < \gamma \leq 1$. The threshold in Equation (10) in the baseline also applies in this extension as it is derived based on the individual projects. Also here, the threshold determines the ranking between the two projects. If $\gamma \leq \gamma*$ the entrepreneur continues to prioritize production in D as in the baseline. If $\gamma > \gamma*$ she produces $\bar{K}$ in project C. In both cases, given the production $\bar{K}$ in project i she chooses the level of production K_j^{SC} in the other project j. She maximizes her utility subject to a tighter lender's IR that reflects banks' internalization of a share of the social costs of production.

$$IR: \; pR(\bar{K} + K_i) - p^2 R_2 \geq K_j k_j + \bar{K} k_i - A + \gamma\theta_d \bar{K} + \gamma\theta_j K_j$$

The equilibrium K_j^{SP} is:

$$K_j^{SP} = \frac{A - \bar{K}\left(\frac{\rho p B}{\Delta p} + k_i + \gamma\theta_i - pR\right)}{\frac{\rho p B}{\Delta p} + k_j + \gamma\theta_j - pR}$$

When $\gamma \leq \gamma*$, the entrepreneur produces K_c^{SP} in project C which is lower than $K*$ also when the entrepreneur can cross pledge due to internalized social costs. If instead, the degree of internalization of social cost γ reaches the threshold γ^*, the entrepreneur produces $\bar{K}$ in project C and K_d^{SP} in project D. These predictions, under cross pledging are aligned with those outlined in the paper under Proposition 2.

In sum cross cross-pledging allows the entrepreneur to achieve a higher level of financing relative to the case where the entrepreneur finances each project individually. However, the mechanisms of winner-picking and constraint-minimization are also present under cross-pledging and lead to equivalent predictions compared to the simpler setting.

Correlated Projects Relaxing the assumption that the projects are perfectly uncorrelated reduces the benefits of cross-pledging. With cross-pledging the entrepreneur is able to access more funding due to economies of diversification. When one of the two projects fails there is still a positive chance to recoup some of the investment costs from the cash flows of the other project. It follows then that assuming perfect correlation completely removes the benefits from cross-pledging. The entrepreneur is then able to borrow as much as in the case of single-project financing.

B Tables and Figures Appendix

Table B1: Variable definitions

Variable name	**Description**
ROA	Ratio of net income to total assets
Emission Intensity	Ratio of EU ETS verified emissions (in 1000 tCO_2) to total assets (in Mil US$). At the parent level, it includes all emissions within the ownership structure of the company (for majority-owned subsidiaries)
Emissions	EU ETS verified emissions (in 1000 tCO_2). At the parent level, it includes all emissions within the ownership structure of the company (for majority-owned subsidiaries)
Ln Total Assets	Natural logarithm of total assets
Ln Debt	Natural logarithm of current and noncurrent liabilities
Ln Equity	Natural logarithm of shareholder funds
Leverage	Ratio of current & noncurrent liabilities to total assets
Interest Ratio	Ratio of interest paid to total assets
Tangibility	Ratio of fixed assets to total assets
Post (EBA)	An indicator for the period following the announcement of the EBA Exercise (2012)
Treated (EBA)	An indicator equal to one for parent firms whose main lenders participated in the EBA Exercise and zero otherwise
Dirty Subs	An indicator equal to one for subsidiaries that own at least one installation in the EU ETS
Dirty Parent	An indicator equal to one for parents that directly own at least one installation in the EU ETS
Distance in Ownership	A variable indicating the distance between the parent and the subsidiary. A value equal to one indicates a direct ownership relation. A value equal to two (or more) indicates that there are intermediate subsidiaries in the ownership chain.

Table B2: Location and Industries

	(1) Parent Level		(2) Dirty Subsidiaries		(3) Clean Subsidiaries	
	Freq.	Percent	Freq.	Percent	Freq.	Percent
Countries						
Austria	32	5.76	12	4.67	166	4.85
Bulgaria	5	0.90	3	1.17	13	0.38
Cyprus	9	1.62			1	0.03
Germany	133	23.92	33	12.84	610	17.83
Denmark	30	5.40	7	2.72	71	2.08
Estonia	2	0.36			8	0.23
Spain	117	21.04	73	28.40	818	23.91
France	59	10.61	27	10.51	349	10.20
United Kingdom	29	5.22	16	6.23	220	6.43
Greece	2	0.36			11	0.32
Croatia	2	0.36			19	0.56
Hungary	13	2.34	4	1.56	36	1.05
Lithuania	3	0.54	5	1.95	19	0.56
Latvia	8	1.44	1	0.39	6	0.18
Malta	5	0.90				
Netherlands	25	4.50	8	3.11	163	4.76
Poland	32	5.76	16	6.23	230	6.72
Portugal	31	5.58	12	4.67	234	6.84
Slovenia	19	3.42	5	1.95	40	1.17
Belgium			4	1.56	64	1.87
Czech Republic			19	7.39	82	2.40
Finland			2	0.78	15	0.44
Italy			1	0.39	104	3.04
Norway			1	0.39	18	0.53
Romania			3	1.17	40	1.17
Sweden			3	1.17	49	1.43
Slovakia			2	0.78	22	0.64
Ireland					7	0.20
Luxembourg					6	0.18
SIC 1 Industry						
Agriculture, Forestry and Fishing	4	0.72	5	1.95	75	2.19
Mining and Construction	17	3.06	7	2.72	319	9.31
Manufacturing (Light)	76	13.67	91	35.41	446	13.02
Manufacturing (Heavy)	51	9.17	63	24.51	345	10.07
Transportation and Public Utilities	71	12.77	79	30.74	886	25.87
Trade	41	7.37	6	2.33	743	21.69
Finance, Insurance and Real Estate	229	41.19				
Services	67	12.05	6	2.34	607	17.73
Observations	556		257		3421	

Table B3: Treated Banks

Panel A: Treated Banks EBA	
Banco Bilbao Vizcaya Argentaria, SA	Landesbank Hessen-Thouringen Girozentrale
Banco Comercial Português SA	Lloyds Banking Group Plc
BNP Paribas SA	Nykredit Realkredit A/S
Banco Popular Espanol SA	Nordea Bank AB
Banco Santander SA	NORD/LB Norddeutsche Landesbank Girozentrale
Bank of Valletta Plc	Nova Kreditna banka Maribor d.d.
Barclays Plc	Nova Ljubljanska Banka d.d.
Crédit Agricole Group	OTP Bank Nyrt.
Danske Bank A/S	Powszechna Kasa Oszczednosci Bank Polski SA
Deutsche Bank AG	Rabobank Group
Deutsche Zentral-Genossenschaftsbank AG	Raiffeisen Bank International AG
DNB Bank ASA	Royal Bank of Scotland Group Plc
Erste Group Bank AG	Skandinaviska Enskilda Banken AB
Espirito Santo Financial Group SA	Société Générale SA
Groupe BPCE	Svenska Handelsbanken AB
HSBC Holdings Plc	Swedbank AB
Intesa Sanpaolo SpA	Sydbank A/S
Jyske Bank A/S	UniCredit SpA
La Caixa	Westdeutsche Genossenschafts-Zentralbank AG

Panel B: Treated Banks Social Preferences

Name	SBTi Join Year
ING Group	2015
BNP Paribas	2016
Credit Agricole CIB	2016
HSBC Banking Group	2016
Societe Generale SA	2016
La Banque Postale	2017
ABN Amro Bank	2018
BBVA	2018
Royal Bank of Scotland	2018
Swedbank AB	2018
Raiffeisen Bank International AG	2018
Novo Banco	2019

Note: This table lists the lenders that are exploited to construct exposure measures in the Credit Crunch (Panel A) and Social Preferences (Panel B) analyses. Panel A lists the banks that participate in the EBA Exercise and are present in the data set used in this analysis. The list covers 38 of the 48 banks used in Gropp et al. (2018). Similarly Panel B lists the banks in the data set that made a SBTi commitment, along with the commitment year. Banks that joined SBTi after the end of the observation period (2019) are not listed. Source for EBA exercise banks: Gropp et al. (2018), Table A1 in the Online Appendix. Source for SBTI commitments: `https://sciencebasedtargets.org/`. Original commitments are confirmed using `https://archive.org/web/` as SBTi removes listed members if after two years they fail to validate their targets.

Table B4: Fixed Effects Cascade for EBA shock

Dependent Variable: Emission Intensity					
	(1)	(2)	(3)	(4)	(5)
Treated	0.058	0.058	0.287	0.145	0.256
	(0.198)	(0.200)	(0.244)	(0.361)	(0.399)
Post	-0.205				
	(0.119)				
Treated × Post	0.468	0.468	0.545	0.811*	0.714*
	(0.309)	(0.310)	(0.386)	(0.423)	(0.354)
Observations	735	735	735	735	735
Year FE	No	Yes	No	No	No
Industry-Year FE	No	No	Yes	Yes	Yes
Country-Year FE	No	No	No	Yes	Yes
Firm Controls	No	No	No	No	Yes
Adjusted R^2	-0.000	-0.003	-0.015	-0.019	0.025
Number of firms	241	241	241	241	241
Clustering	Country	Country	Country	Country	Country

Dependent Variable: ROA					
	(1)	(2)	(3)	(4)	(5)
Treated	-0.004	-0.004	-0.005	-0.004	-0.002
	(0.003)	(0.003)	(0.004)	(0.005)	(0.006)
Post	-0.008**				
	(0.003)				
Treated × Post	0.015*	0.015*	0.014	0.024***	0.021***
	(0.007)	(0.008)	(0.008)	(0.005)	(0.004)
Observations	735	735	735	735	735
Year FE	No	Yes	No	No	No
Industry-Year FE	No	No	Yes	Yes	Yes
Country-Year FE	No	No	No	Yes	Yes
Firm Controls	No	No	No	No	Yes
Adjusted R^2	0.002	0.005	0.044	0.046	0.158
Number of firms	241	241	241	241	241
Clustering	Country	Country	Country	Country	Country

Note: This table sequentially introduces the fixed effects and firm controls in less stringent specifications compared to Equation (12) for the two main variables in the analysis. The dependent variable is indicated in the column header. *Treated* assumes a value of one for parent firms whose main lenders participated in the EBA Exercise and zero otherwise. *Post* indicates the period following the announcement of the EBA Exercise. Firm controls are averages over the pre-shock period and include Ln Total Assets, Tangibility, and Leverage.

Table B5: Alternative Treatment Definitions for EBA shock

Panel A: Continuous Treatment			
	(1) Ln Debt	(2) ROA	(3) Emission Intensity
EBA Exposure × Post	-0.307**	0.025***	0.306*
	(0.124)	(0.003)	(0.168)
Observations	735	735	735
Firm FE	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes
Adjusted R^2	0.965	0.517	0.929
Number of firms	241	241	241
Clustering	Country	Country	Country

Panel B: Treated only by parent banks			
	(1) Ln Debt	(2) ROA	(3) Emission Intensity
Treated by Parent × Post	-0.215**	0.011***	0.090**
	(0.078)	(0.003)	(0.036)
Observations	612	612	612
Firm FE	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes
Adjusted R^2	0.966	0.521	0.849
Number of firms	199	199	199
Clustering	Country	Country	Country

Note: This table estimates the impact of the EBA capital exercise on debt levels and the main dependent variables with different definitions of treatment. The main regression is estimated as in Equation (12), besides the treatment definition. The dependent variable is indicated in the column header. *EBA Exposure* in Panel A is a continuous exposure measure to treatment between 0 and 1. It reports the share of lenders that participated in the EBA Exercise for each parent firm, In Panel B, I drop firms that only borrow from subsidiaries of banks that participate in the Exercise. *Post* indicates the period following the announcement of the EBA Exercise.

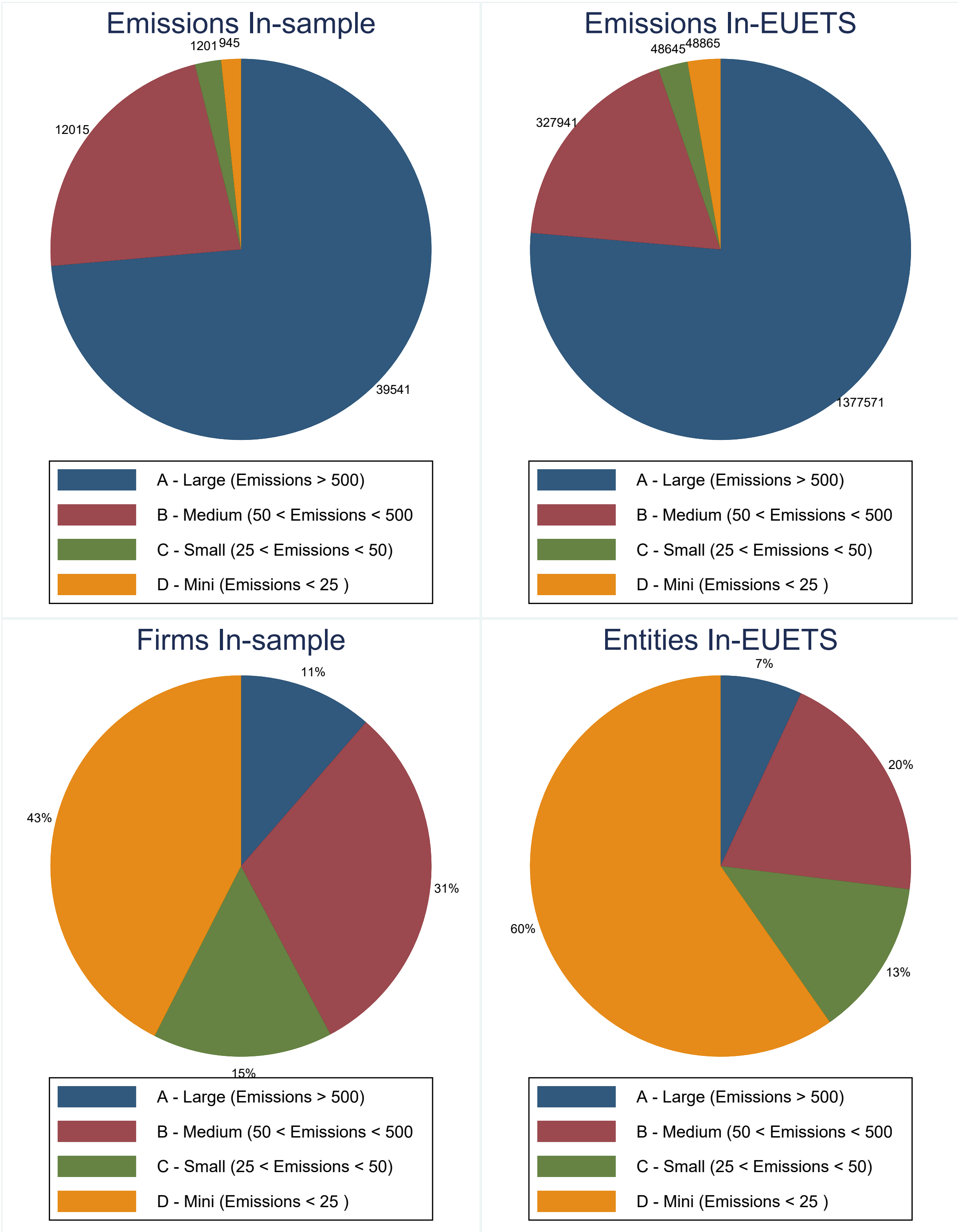

Figure B1: Sample representativeness with respect to EU ETS Firms

Note: Charts depict the sample representativeness with respect to firms in the EU ETS. Data is averaged across the sample period (2009-2019). Summary statistics for the EU ETS are from the European Environment Agency EU ETS data viewer (Link Firms are grouped in categories A to D depending on emission levels as indicated. Sample firms are around 3% of EU ETS entities.

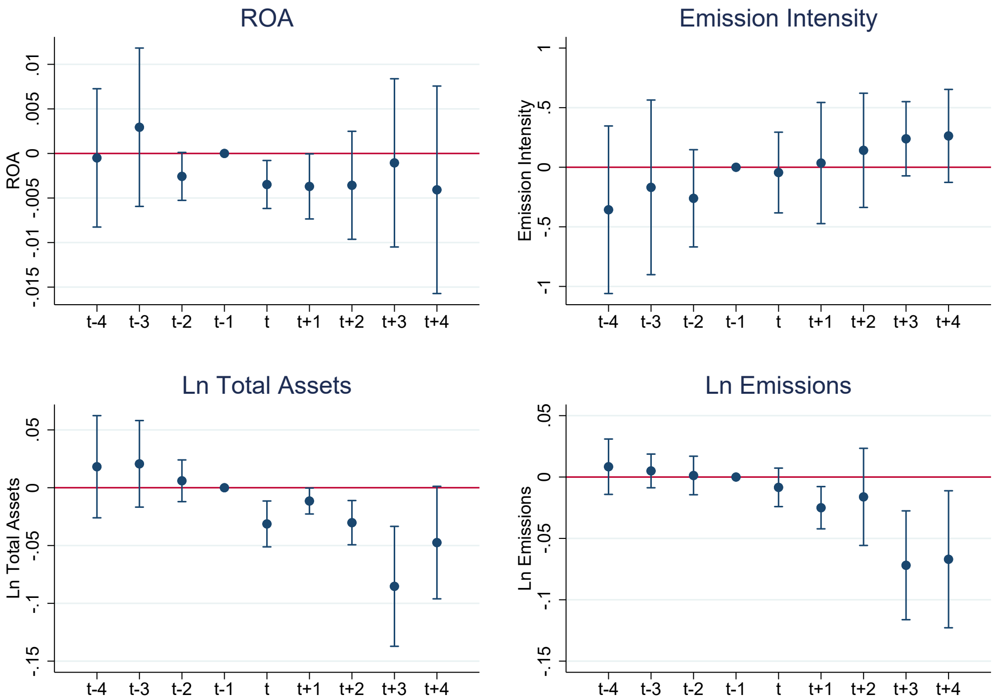

Figure B2: Social Preferences: Longer treatment period

Note: The graphs depict the social preferences event study using an extra lead and lag compared to the baseline for the two main variables in the analysis in the top graphs (ROA and Emission Intensity) as well as the decomposition of the effect on emission intensity in the bottom two graphs (Ln Total Assets and Ln Emissions). Similar to Equation (13) but with 4 leads and 4 lags instead of 3, each specification includes firm, industry-year, as well as country-year fixed effects. Standard errors are clustered at country level. Coefficient estimates are surrounded by 95% confidence bands.

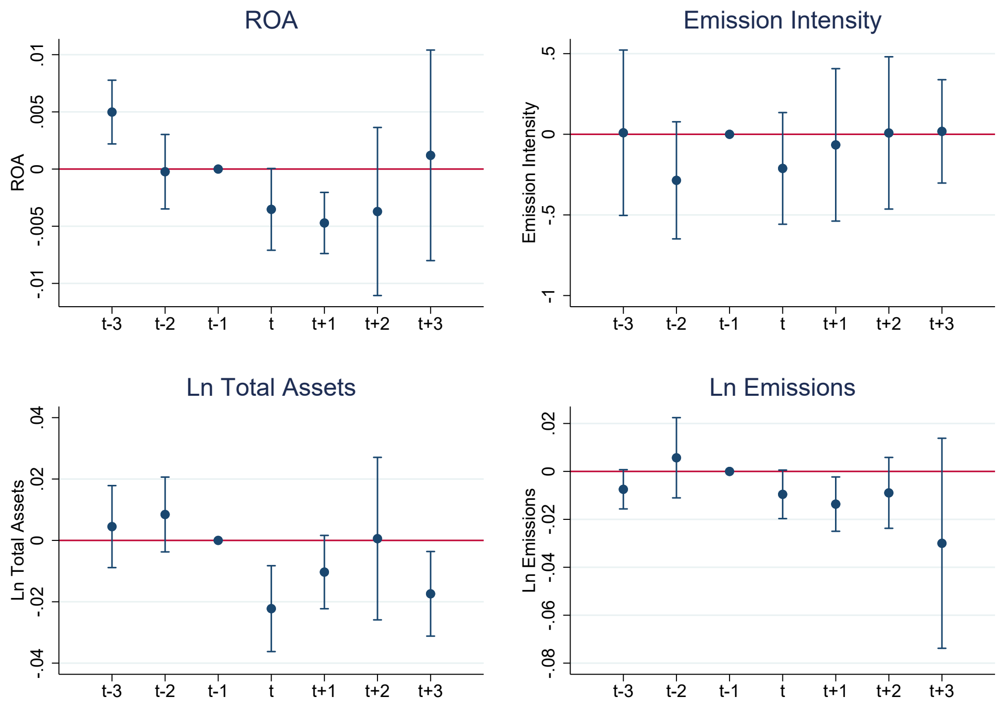

Figure B3: Social Preferences: Stacking as in Cengiz et al. (2019)

Note: The graphs depict the social preferences event study using the stacking methodology proposed in Cengiz et al. (2019) for the two main variables in the analysis in the top graphs (ROA and Emission Intensity) as well as the decomposition of the effect on emission intensity in the bottom two graphs (Ln Total Assets and Ln Emissions). As the main regression specification is as in Equation (13), each specification includes firm, industry-year, as well as country-year fixed effects. Standard errors are clustered at country level. Coefficient estimates are surrounded by 95% confidence bands.